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The Influence of Player Load on Injury Risk in Professional Rugby Union Players

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THE INFLUENCE OF PLAYER LOAD ON INJURY RISK IN PROFESSIONAL RUGBY UNION PLAYERS

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I am the author of this thesis, and the work described therein was carried out by myself personally.

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PUBLICATIONS

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West, S.W., Williams, S., Kemp, S.P.T., Cross, M.J., McKay, C., Fuller, C.W., Taylor, A., Brooks, J.H.M. & Stokes, K.A. (2019). Patterns of training volume and injury risk in elite rugby union: an analysis of 1.4 million hours of training exposure over eleven seasons. *Journal of Sports Sciences.* [in press].

CONFERENCE PRESENTATIONS

West, S. Training loads associated with sevens rugby union. *Rugby Science Network Conference*. September 2016. Bath, UK. [Oral presentation]

West, S., Williams, S., Cross, M.J., Howells, D., Mobed, R., Kemp, S.P.T. & Stokes, K.A. Workload spikes combined with high cumulative load is associated with increased injury risk in elite rugby sevens players. *IOC World Conference on Prevention of Injury and Illness in Sport.* March 2017. Monaco. [Poster presentation]

West, S. Training load and injury risk in English professional rugby union. *Rugby Science Network Conference*. September 2017. Bath, UK. [Oral presentation].

West, S. How to get the most of monitoring data: the rugby union experience. *XXVIII Isokinetic Medical Group Conference.* April 2019. London, UK. [Oral presentation].

ABSTRACT

The rate of injury in professional rugby union is high compared to that of other team sports. As such, the need for injury mitigation strategies is evident. One emerging approach is the appropriate management of player load, with multiple studies across different sports demonstrating the association between load and injury risk. The aim of this thesis, therefore, is to build upon the small amount of work undertaken in rugby union to further our understanding of this modifiable risk factor to aid governing bodies and club practitioners make informed decisions around player loading patterns.

The first experimental study in this thesis (Chapter Three) shows that over an eleven-season period training volume per player per week has remained stable. Over the same period, training injury incidence has also remained stable. However, injury severity has risen dramatically, with an injured player in the 2017/18 season missing an average of 20 extra days absence compared to an injured player in the 2007/08 season. Chapter Four demonstrates the clear association between weekly injury burden and team performance, as well as between training load and injury burden. No clear associations between training load and performance were evident. Chapter Five examines some commonly used methods for calculating the acute:chronic workload ratio training load metric. This investigation revealed that in the case of rugby union, despite club-by-club variation, a coupled and exponentially weighted 3 to 14 day acute:chronic workload ratio was the best fit for modelling injury data. Using this load measurement, calculated from session Rating of Perceived Exertion (sRPE) data, Chapter Six outlines a clear association between low acute:chronic values and injury risk when examining all injury types and non-contact soft tissue injuries in isolation. Acute:chronic workload ratio values of 1.26 were associated with "*likely"* beneficial effects, compared to a median value of 0.82 for both all injury and non-contact soft tissue injuries. Chapter Seven reports the current landscape of monitoring in professional rugby union in England, with widespread variation in the value placed on load monitoring metrics by clubs as well as extensive differences in the methods used to capture those metrics. This study was used to inform the final study of this thesis by identifying a group of clubs using similar load monitoring measurement tools. Chapter Eight provides evidence that both sRPE and Global Positioning System (GPS) data show clear associations with injury risk when aggregated using the acute:chronic workload ratio. Despite this, this Chapter also suggests the minimal added value of using both metrics, with similar Area Under the Curve values achieved when modelling with the "total distance" GPS metric or sRPE metric alone.

In summary, this thesis outlines the importance of player load as a modifiable injury risk factor in professional rugby union, identifying some key methodological steps for maximising the utility of the data collected in practice, including differences between team and individual level data as well as differing methods for capturing the same training load measures. This thesis also explores

the utility of multiple load measurement types spanning from basic measures of training volume to more complex internal (sRPE) and external (GPS) measurement. The findings of this thesis demonstrate a clear link between both sRPE and GPS training load metrics and injury risk, with low acute:chronic workload values associated with an increased risk. This study is the largest of its type across sport and demonstrates the potential utility of managing training load to reduce injury risk in professional rugby union.

LIST OF ABBREVIATIONS

ACWR	Acute: chronic workload ratio
AIC	Akaike Information Criterion
AU	Arbitrary Units
CI	Confidence Interval
EWMA	Exponentially weighted moving average
GPS	Global Positioning System
HSR	High Speed Running Distance
MBI	Magnitude Based Inferences
MD23	Match Day 23
PRISP	Professional Rugby Injury Surveillance Project
RPE	Rating of Perceived Exertion
SD	Standard Deviation
sRPE	Otherwise known as sRPE TRIMP (Rating of Perceived Exertion x session duration in minutes)
TD	Total Distance

CHAPTER 1

Introduction

Rugby union is a collision-based team sport that originated in the early 1820's in England as a derivative of association football. The sport's worldwide popularity has grown in recent years with the governing body, World Rugby, reporting over 7 million players across 120 countries worldwide (World Rugby, 2018). Rugby Union matches are 80 minutes in length, comprising of two halves of 40 minutes. The aim of the game is to progress the ball over the opposition try line by running with the ball, kicking or passing (backwards only) to a member of your team (Comfort, 2015). Points are awarded with different values for a try (5 points), conversion (2 points), penalty (3 points) or a drop kick (3 points). Rugby Union can be further divided into two formats, which are the traditional 15-a-side game, as well as the 7-a-side format. The former is described as a game composed of short intermittent bouts of maximal or high intensity exercise interspersed with bouts of lower intensity exercise or rest (Nicholas, 1997). Within a 15-a-side Rugby Union team, two broad positional groupings can be seen, backs and forwards, of which there are seven and eight players, respectively. Within the 7-a-side format, 3 players are designated as forwards with 4 as backs however, the distinction between the two groups is less apparent in Sevens compared to traditional 15-a-side rugby (Fuller, Taylor and Molloy, 2010).

Since professionalisation in 1995, rugby union has seen marked changes in the demands of the sport, with large changes apparent in match play specifically (through increased match events such as tackles), but also in the season length and structure, with players potentially exposed to over 30 games per season over a ten month period (Quarrie and Hopkins, 2007; Quarrie et al., 2016; Williams et al., 2017c). Given the nature of the sport, the demands of rugby union are often described in terms of both the contact and running demands. In general, the running demands of the game are higher in backs, while the contact demands are greater in forwards (Cunniffe, Proctor, Baker and Davies, 2009; Dubois et al., 2017; Quarrie, Hopkins, Anthony and Gill, 2013). On average, players are reported to cover distances of between 5400 and 6300 m in international rugby (Quarrie et al., 2013) and ~7000 m in professional club rugby (Cunniffe et al., 2009), with backs covering greater distances at higher speeds (Quarrie et al., 2013; Dubois et al., 2017) and forwards spending a greater amount of time jogging (Cunniffe et al., 2009). In contrast to running demands, forwards were seen to be exposed to greater contact demands than that of backs, with these demands made up of scrums, rucks, tackles and mauls (Quarrie et al., 2013). Whilst games last 80 mins, ball-in-play time during this 80 minutes is reported as an average of 36.21 ± 2.40 mins (Quarrie et al., 2013). Despite this, it is clear that the physiological demands during match play are high, with 42 ± 17% of the 80 minute match spent at above 85% of heart rate max (Dubois et al., 2017). These figures provide useful context as to the average demands of rugby union match play but as technology has improved in recent seasons, there has been a growing interest in the longest periods of ball-in-play in rugby union, which represent a "worst-case-scenario" (Reardon, Tobin, Tierney and Delahunt, 2017; Cunningham et al., 2018). Studies in this area have shown that the differences between positional groups shown by average demands data are only perpetuated when examining "worst-case-scenarios" and, therefore, have been used to guide training prescription specific to these groups (Reardon et al., 2017).

An area of increasing scrutiny within rugby union relates to the injury risk associated with participation. A 2013 meta-analysis reported a rate of 81 injuries per 1000 hours of match exposure and 3 per 1000 hours in training for the professional game (Williams, Trewartha, Kemp and Stokes, 2013), while the most recent data on injury risk within professional club rugby in South Africa and England reported match incidences of 100 per 1000 hours and 92 per 1000 hours, respectively (Schwellnus et al., 2018; Kemp et al., 2019). With the increase in publicity surrounding these injury figures (Peters, 2018b), there have been calls for action to reduce the risk within the sport (Peters, 2018a; Aylwin, 2016). Further to this, a recent study reported the potential long term consequences of rugby participation, highlighting a significantly greater risk for osteoarthritis, joint replacement, osteoporosis and anxiety in former players (Davies et al., 2017). Given these figures, the question of acceptable injury risk arises with Webborn (2012) highlighting an employer's ethical responsibility to maintain the welfare of its employees, which in this context is the modern day professional rugby player. Furthermore, Drawer and Fuller (2002) suggest that when evaluated, the level of risk associated with professional sports participation would be found to be unacceptable in the context of wider workplace health and safety.

The aim of any research regarding risk factors for injury is to improve the welfare of the athletes of that sport; however, the knock-on effect of any such prevention measure upon player and team performance must also be considered, especially in professional sport. Reductions in injury burden have previously been shown to positively impact upon team success in rugby union (Williams et al., 2015); however, there is currently a dearth of evidence investigating the effect of training load on both injury burden and performance. Although difficult to quantify in a team sport setting, performance can be measured as either a behaviour or an outcome. As a behaviour, performance may represent a key performance indicator (Drew, Raysmith and Charlton, 2017c; Bennett, Bezodis, Shearer, Locke and Kilduff, 2018) or a high subjective rating (Ekstrand, Walden and Hagglund, 2004). As an outcome, performance may represent final league position (Brooks, Fuller, Kemp and Reddin, 2008) or the winning of a specific event or competition (Drew et al., 2017c). Regardless of the metric used to assess performance, the utility of any measure representing a change in injury risk must also be assessed for its subsequent effect on performance.

Injury prevention in sport can be addressed from a primary, secondary or tertiary perspective (Drew, Cook and Finch, 2016). In an effort to reduce rates of injury across the game, in recent years a number of injury prevention strategies have been introduced, including law changes (Cazzola, Preatoni, Stokes, England and Trewartha, 2014; Tucker et al., 2017) and load management guidelines (Quarrie et al., 2016). Injury aetiology is a highly complex and dynamic process, which can be influenced by a number of intrinsic and extrinsic risk factors (Meeuwisse et al., 2007). The load management strategies and principles outlined by Quarrie et al. (2016) can be implemented at each of the primary, secondary and tertiary stages of prevention. A clear representation of how workloads influence the dynamic recursive model of Meeuwisse et al. (2007) has been outlined by Windt and Gabbett (2016). In addition, the association between training load and injury has been demonstrated through systematic reviews (Drew and Finch, 2016; Jones, Griffiths and Mellalieu, 2017; Eckard, Padua, Hearn, Pexa and Frank, 2018) and, therefore, the need for more research of this type specifically targeted at rugby union populations is required. To date, there is a relative sparsity of studies examining the relationship between training load and injury risk in elite rugby union (Cross, Williams, Trewartha, Kemp and Stokes, 2016b) and, therefore, the aim of this PhD thesis is to examine this relationship in closer detail, and to provide generalizable results to teams across professional rugby union that could potentially inform practice and lead to a reduction in injury burden within the sport.

Accordingly, the following research questions will be addressed in this thesis:

1. Have training volumes and training injury risk changed over time in professional rugby union?
2. Are there associations between training load, injury burden and performance in rugby union at a team average level?
3. What are the best methods when using session Rating of Perceived Exertion (sRPE) data to inform practitioners on injury risk management in rugby union? The three methods specifically targeted, which concern the calculation of an acute: chronic workload ratio are:
    a. Exponentially weighted moving averages versus rolling averages
    b. Acute and chronic time windows used
    c. Coupled or uncoupled ratios
4. What is the relationship between sRPE derived training load and risk of injury in professional rugby union?
5. What is the value placed on monitoring variables by clubs when making decisions on injury risk and player performance, and are the methods by which these variables are collected common across all clubs?
6. Does the addition of external load measurement tools (in the form of Global Positioning Systems (GPS) data) provide additional insight, over and above sRPE, on the relationship between training load and injury risk in professional rugby union?

CHAPTER 2

Review of Literature

2.1 Outline

This chapter will provide a summary of the literature surrounding the management of training load in sport as a management tool to mitigate against injury risk. Having outlined some key principles regarding the definition, impact, causation, theory and risk factors for injury, the review will then outline the evidence for training load as a modifiable risk factor that can be targeted for injury prevention strategies in the context of rugby union. Key aspects including the origins, measurement, quantification, and issues surrounding the capture and use of training load data will be addressed. This field is rapidly evolving and the application of such techniques in a rugby union setting has been limited to a small number of studies. This review will build on these studies and draw on the findings from research across other sports to establish the relative importance of training load as a risk factor for injury in rugby union.

2.2 Context

Despite the health benefits associated with participation in sport and recreational exercise, it must also be recognised that sports represents a risk to health in the form of injury (Van Mechelen et al., 1992; Webborn, 2012). In the context of professional rugby union, where injury risk is known to be high compared with other sports (Williams et al., 2013), it is important to consider the role of governing bodies and clubs as employers of athletes (Drawer and Fuller, 2002; Webborn, 2012). From this perspective, it is the responsibility of these employers to ensure that the health, safety, and welfare of players is maintained during participation, while from an athletes perspective, it is important that they themselves accept and are aware of the risks inherent to participation in sport (Drawer and Fuller, 2002; Webborn, 2012). The consequences of sports injury are wide-ranging and evident for both the players and teams for whom they play. For a team, Drawer (2001) outlines the "cost" of injury as both indirect and direct. Whilst clearly there is a direct financial cost of injury by way of salary and medical expenses, the indirect costs of losing an important player (e.g., upon performance, crowd attendances, and broadcasting revenues) are more difficult to capture. The consequences from an athlete perspective can be seen as both short and long term, with the long term consequences of a professional rugby union career recently outlined as both beneficial to one's health (through a reduction in diabetes risk) but also harmful (increase in osteoarthritis, joint replacement and osteoporosis) (Davies et al., 2017). The successful recognition and implementation of injury mitigation strategies can, therefore, be seen as crucial, to not only improve player welfare but for the financial and on-pitch success of their respective teams. This has been demonstrated in a youth ice hockey context, through an economic evaluation of the effect of introducing a body checking law change to reduce injury risk. This study demonstrated a 2.5 times lower healthcare cost as a consequence of the law change made (Lacny et al., 2014). Not only has reducing injury risk been shown to reduce economic cost, but it has also been shown that reducing one's injury burden increases the likelihood of team success in multiple sports (Drew et al., 2017c) including rugby union (Williams et al., 2015). Given this, the identification of any risk factors that can be easily modified to minimise injury risk is of paramount importance to ensure the welfare and career longevity of the players at both the elite and recreational levels of rugby union.

2.3 Injury Defined

In order to better understand injury risk and to put in place measures to reduce this risk, epidemiological studies are required to establish the number and types of injuries experienced in a sports setting (Van Mechelen et al., 1992; Finch, 2006). The data supplied by studies of this nature are vital to the development, treatment, and rehabilitation of injury and, therefore, it is of the utmost importance that the methodology in injury surveillance studies is of a high enough quality to ensure accurate data is captured (Brooks and Fuller, 2006). A 2016 review of surveillance systems in sport found 15 largescale injury surveillance systems to be in place, most of which were at the professional/ elite level of sport (Ekegren, Gabbe and Finch, 2016). Despite these systems providing the same role of injury surveillance, comparison between studies is difficult due to differences in methodology including injury definitions, personnel recruited to capture data and differences in the tools used to collect data (Ekegren et al., 2016). Further to this, Brooks and Fuller (2006) have highlighted other issues including differences in the calculation of injury incidence, with values presented as both number of injuries per 1000 hours and per 1000 exposures in different environments. While injury definitions used in sports injury research include "any physical complaint", "medical attention" and "time loss" (Clarsen, Myklebust and Bahr, 2013), given the variability associated with injury surveillance studies in rugby related research, Fuller et al. (2007c) outlined a consensus on definitions and data collection procedures in the context of rugby union. For the purposes of injury data capture, a time loss definition was accepted as "an injury that resulted in a player being unable to take a full part in future rugby training or match play for more than 24 hours from midnight at the end of the day the injury was sustained*"* (Fuller et al., 2007c). This definition has since been shown to provide a good balance between reporting reliability and accurate representation of injury risk and clinical demand, compared with a 7-day time loss definition (Cross et al., 2018). While a 7-day time loss definition enables a small reduction in between-team variance, this reduction was not deemed large enough to justify its use due to the loss in accuracy of risk representation and clinical demand (Cross et al., 2018). For the successful implementation of injury surveillance, it is important to tailor the surveillance methodology to the needs of the population while accounting for resource availability.

2.4 Injury Prevention Models

In professional sport, where the negative consequences of injury can be extensive, including a decrease in performance, financial and legal issues as well as long term health consequences, a greater understanding of how injury prevention strategies can improve players welfare is required. The extent of the sports injury problem calls for preventative actions to occur in order to reduce this risk, with these actions to be guided by the results of epidemiological studies (Van Mechelen et al., 1992). To do this, one must understand current models of injury prevention, which provide a framework for conducting research into sports injury. This section provides a brief overview of some of the key frameworks and models that have guided injury prevention research, as well as a greater understanding of the factors that lead to sports injury.

2.4.1 Sequence of prevention model

One of the first and most commonly cited models for sports injury prevention is that of Van Mechelen (1992) (Figure 2.1). This model was first proposed in 1987 by Van Mechelen as the 'sequence of prevention' and outlined four key steps to prevent injury. The first step in the cycle is to identify and describe the problem of interest. The second step is to identify potential factors or mechanisms that play a role in the onset of injury. These first two steps can be completed using epidemiological studies whereby the incidence, severity and burden of specific injury types, sites, mechanisms and risk factors can be collected, analysed and targeted. Step 3 of the model involves the introduction of preventative measures to the population of interest to try to reduce the risk or severity of injuries within this group. The final step revisits the first step and is designed to identify the impact of the measures introduced in Step 3. In the context of rugby union, there is an abundance of epidemiological studies targeting stages one and two of the cycle (Brooks, Fuller, Kemp and Reddin, 2005a; Brooks, Fuller, Kemp and Reddin, 2005b; Williams et al., 2013; Schwellnus et al., 2018), while steps 3 and 4 have also been targeted with the introduction of injury prevention measures such as movement control exercise programmes (Hislop et al., 2017; Attwood, Roberts, Trewartha, England and Stokes, 2017) and law change (Cazzola et al., 2014).

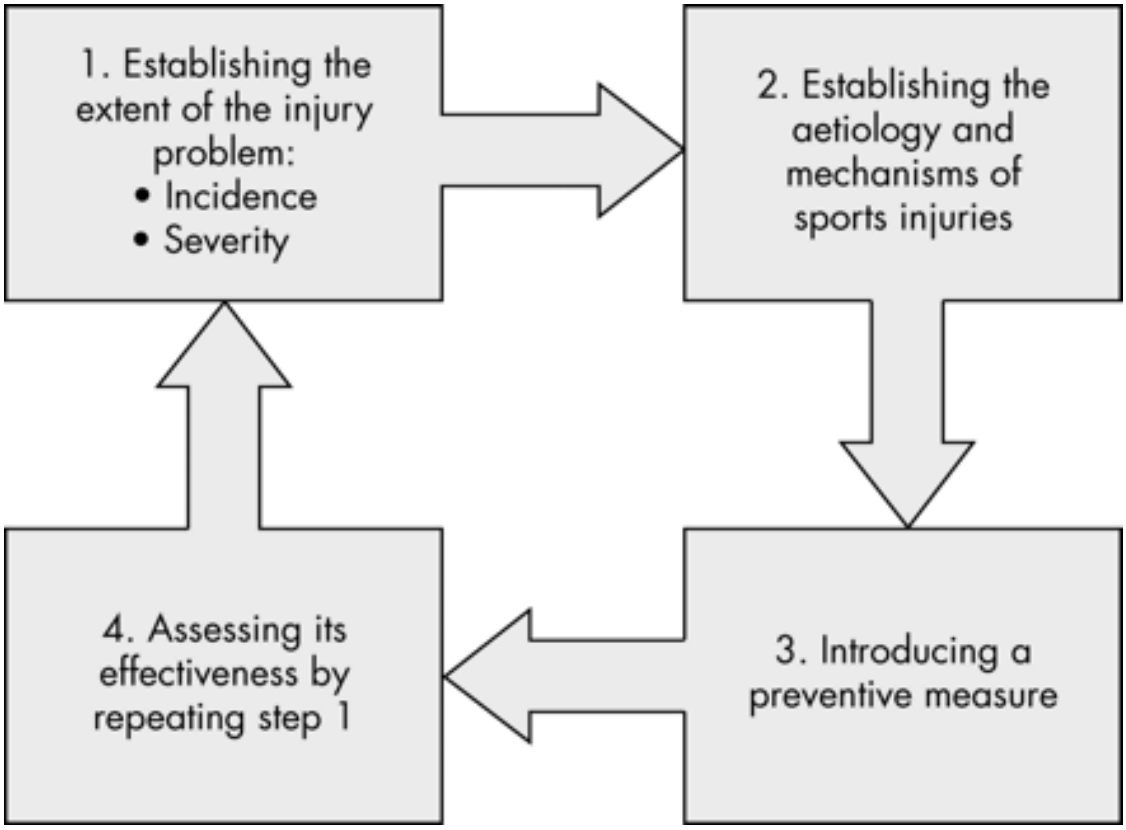

Figure 2.1: Sequence of prevention model (Van Mechelen et al., 1992)

2.4.2 Translating research into injury prevention practice framework

While Van Mechelen's model provides a useful framework for guiding injury prevention research, the model does not address issues surrounding the implementation of preventative measures (Finch, 2006). Given this, in 2006, a new model for injury prevention was introduced to build on the Van Mechelen model by providing a greater understanding on the implementation context within which the measures were to be introduced (Finch, 2006). Similarly to Van Mechelen, Finch's Translating Research into Injury Prevention Practice (TRIPP) model's first two steps use injury surveillance to establish and understand the incidence, severity, aetiology and mechanisms of injury. Step 3 of TRIPP is to identify potential solutions and to develop suitable prevention measures that are evidence-based and consider the disciplines central to injury prevention, including biomechanics, health promotion, behavioural psychology and sports medicine. These preventative measures should be targeted upon the injuries or mechanisms identified in part 2 as a priority for injury risk management. Step 4 describes the efficacy of the intervention identified in Step 3 and evaluates the measure's efficacy in the context of ideal conditions. This step is often undertaken in a controlled manner whereby conditions of the measure are highly controlled, potentially in a laboratory setting and with a small number of participants. Step 5 aims to understand how the outcomes of step 4 can be translated into the real world setting of sporting behaviours. Crucial to this stage is the development and understanding of the implementation context, so that barriers and facilitators to the prevention measure are addressed to ensure the successful implementation of the measure in the real world. Finally, Step 6 involves the implementation of the intervention in the desired setting and evaluation of the effectiveness of the intervention. Figure 2.2 provides a visual comparison of the models of Van Mechelen and Finch and highlights the differences between the two. Although Steps 1 and 2 as well as the final stage in each model are similar, the TRIPP model encourages consideration of the implementation context, and therefore, should be adopted when planning or implementing injury prevention measures.

Model stage	TRIPP	van Mechelen et al 4 stage approach [1]
1	Injury surveillance	Establish extent of the problem
2	Establish aetiology and mechanisms of injury	Establish aetiology and mechanisms of injury
3	Develop preventive measures	Introduce preventive measures
4	"Ideal conditions"/scientific evaluation	Assess their effectiveness by repeating stage 1
5	Describe intervention context to inform implementation strategies	
6	Evaluate effectiveness of preventive measures in implementation context	

Figure 2.2: A comparison of Finch's (2006) TRIPP 6 stage model with that of Van Mechelen (1992) 4 stage injury prevention model measure

2.4.3 Multifactorial model of injury aetiology

To go beyond the models aimed at preventing injuries one must better understand the aetiology of an injury. Based on models developed to explain how disease manifested itself, Meeuwisse (1994) similarly presents the aetiology of injury as a multifactorial process, and not as a univariate analysis of risk. Meeuwisse (1994) proposed that for an injury to occur, a number of factors interact to produce the negative injury outcome. These factors can be broadly grouped into intrinsic and extrinsic factors. Intrinsic risk factors are those that are internal to the specific athlete, such as biomechanics, conditioning, and age, while extrinsic risk factors are those that are external to the athlete, such as the weather, field conditions, rules and equipment. Intrinsic risk factors are experienced to a different degree by each athlete and predispose them to injury; however, in isolation they are unlikely to cause an injury to occur. This is comparable to extrinsic factors, which may act upon the athlete when exposed to sport but are unlikely to cause injury themselves. In the presence of both intrinsic and extrinsic risk factors and the interaction between them, an athlete is susceptible to injury, whereupon should an inciting event occur, it is then that an injury may be the outcome. Historically, the aim of practitioners is to try to focus on minimising the inciting events and mechanisms of injury, although Meeuwisse (1994) also emphasises the importance of the factors further down the chain (i.e., injury risk factors) as targets for prevention programmes.

2.4.4 A cyclical operational model to investigate contact sports injuries

Despite the valuable contribution of the Meeuwisse model (1994), Gissane, White, Kerr and Jennings (2001) outline the issue of considering injury aetiology as a linear model with a defined start and finish point, when in fact the likelihood is that risk factors for injury are likely to change with time, making it a cyclical process. The cyclical model introduced by Gissane, White, Kerr and Jennings is similar to that of the multifactorial model in that an athlete starts the cycle in a fit and healthy state while being predisposed due to a number of intrinsic and extrinsic risk factors. On exposure to a potential injury event, players can complete the event without injury and return to their original state or they can become injured. At this point the multifactorial model ends; however, the cyclical model expands on this by outlining 3 potential outcomes for the injured player. Firstly, after sustaining the initial injury and a period of rehabilitation, a player may suffer a re-injury, meaning a further period of rehabilitation occurs. The second outcome is for the athlete to re-enter sports participation, but at a lower level. Finally and in the majority of cases, a player will return to full participation. While the initial multifactorial model (Meeuwisse, 1994) described the introduction of intrinsic and extrinsic risk factors, the cyclical model expanded on the outcomes for a player post injury that more appropriately represents the non-linearity of the injury process.

2.4.5 A dynamic, recursive model of aetiology in sport injury

Following the proposition of a non-linear model, Meeuwisse et al. (2007) revisited the original multifactorial model to account for the consequences of repeated participation with and without the presence of injury. The newly proposed dynamic recursive model of injury aetiology accounts for both the intrinsic and extrinsic risk factors for injury as well as the repeated nature of sporting participation (Figure 2.3). Furthermore, the model outlines how repeated participation can alter the extrinsic and intrinsic risk factors both when sporting participation leads to injury or non-injury. For example, when a susceptible player is exposed to an inciting event that leads to injury, after a period away from full participation when the player returns to play, the player is now a predisposed athlete with the added intrinsic risk factor of a previous injury. A real-world rugby union example of this cycle is presented by Cross et al. (2015), where a player who has suffered a concussion, returns to play after a period of absence with a new intrinsic risk factor (a previous concussion) that increases their internal risk of a subsequent injury by 60%. While the content of this updated dynamic recursive model of injury aetiology features similar content to those preceding it, the authors note that to capture a greater understanding of injury, research must look beyond the initial risk factors and consider the consequences of those risk factors through preceding cycles of participation, whether the outcome was injury or not.

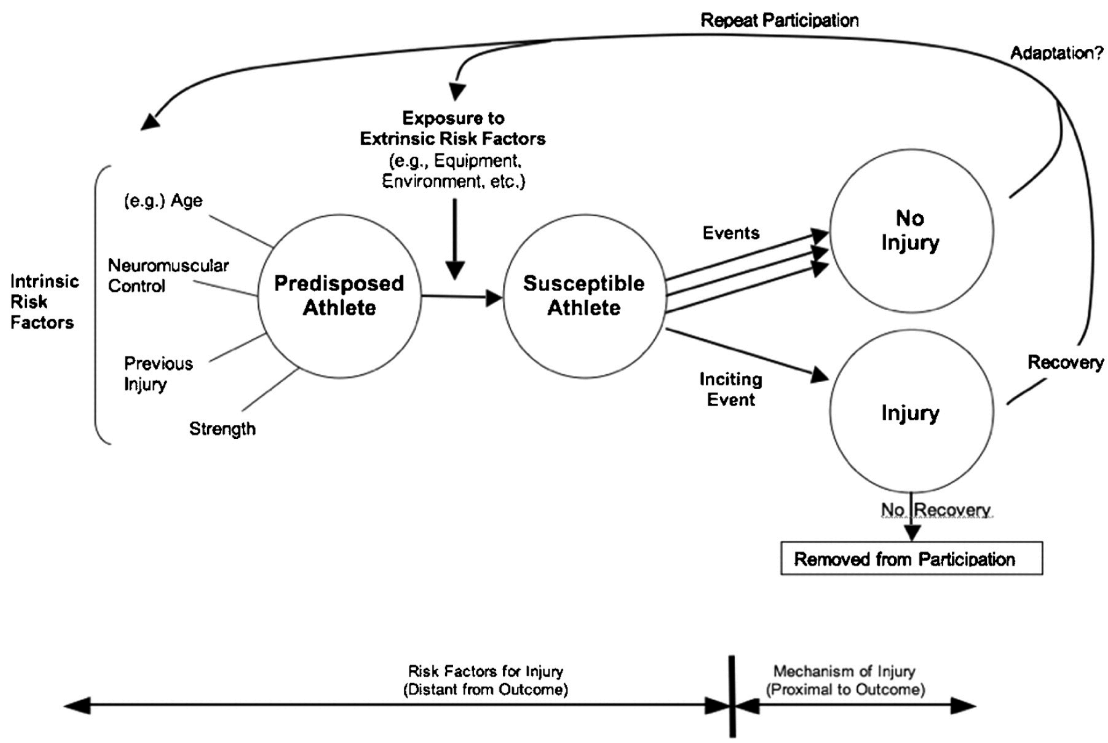

Figure 2.3: A dynamic, recursive model of aetiology in sport injury (Meeuwisse et al., 2007)

2.4.6 Complex Systems theory

More recently, a new theory to further understand the dynamic and highly complex nature of injury has been suggested by multiple authors in the form of complex systems theory (Hulme and Finch, 2015; Bittencourt et al., 2016; Bekker and Clark, 2016). Despite providing a sound attempt to advance initial linear and static models, Hulme and Finch (2015) and Bittencourt et al. (2016) argue that the dynamic recursive model of Meeuwisse et al. (2007) does not adequately describe the complex interactions between the influencing factors. Previous models of injury aetiology investigations are seen by Bittencourt et al. (2016) as a reductionist view whereby injury is simplified into units and considered as the sum of individual basic parts. In contrast, complex systems consider the injury as a whole, with units (parts) that interact with one another in a complex, unpredictable and constantly evolving way (Bittencourt et al., 2016). The defining features of these systems are their dynamic and open structure, which display inherent non-linearity due to the number of recursive loops and the complex interaction between units (Bittencourt et al., 2016). The complexity of the system and the way in which these parts interact and lead to injury has been coined as the web of determinants, in which interactions between parts may be linked in a non-linear manner, meaning small changes in one component may lead to large changes in others (Figure 2.4). Despite the end result (an anterior cruciate ligament (ACL) injury) being the same in both case A (a basketball player) and case B (a ballet dancer), figure 2.4 shows how, in a complex system, the web of determinants can be different in two cases, with certain units having a greater influence over the final outcome than others.

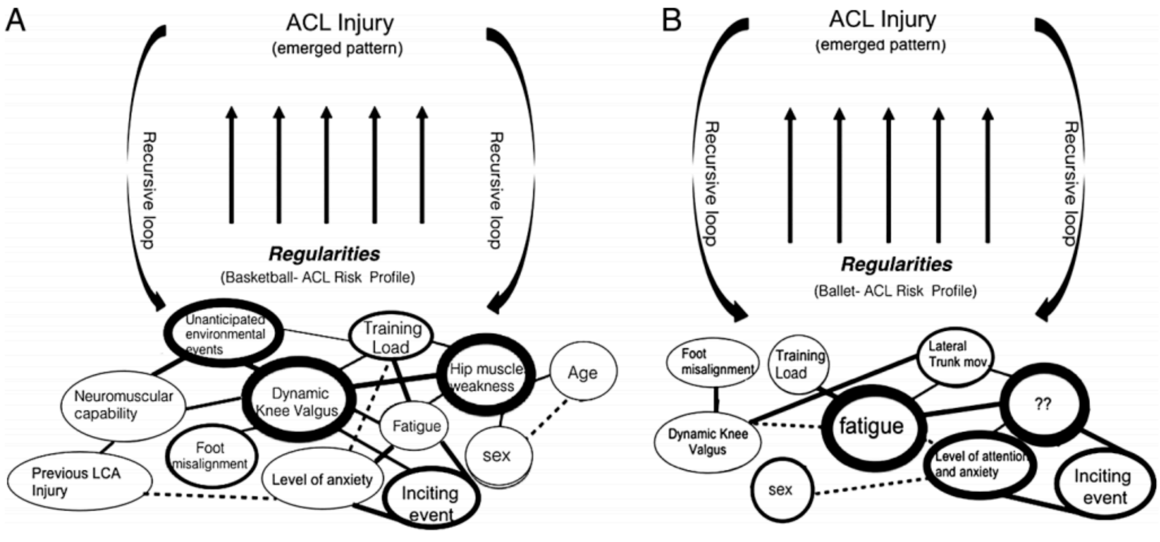

Figure 2.4: Examples of complex systems theory including the web of determinants in injury aetiology for A- a basketball player and B- a ballet dancer. (Bittencourt et al., 2016).

While it seems a logical next step for injury aetiology investigations to incorporate these complex and non-linear relationships between each part of the web of determinants, currently there is limited ability to produce a model that has both the statistical precision as well as the ecological realism required to utilise this complex systems theory (Hulme and Finch, 2015). Although Hulme and colleagues have gone on to produce a further paper on this theory as a practical starting point for further, more sophisticated analysis to be guided by, the utilisation of complex theory has not been widely adopted and has been suggested as a complementary/alternative methodological approach for sports injury research (Hulme, Thompson, Nielsen, Read and Salmon, 2018). In its current state, complexity theory provides a useful framework to guide sports injury research through studying a system as a whole instead of isolating relationships between individual factors; however, it is acknowledged that until such time that the intricate nuances of applying complex theory are understood, traditional approaches should be used while embracing the possibilities of a systems-thinking approach (Hulme and Finch, 2015).

2.4.7 Summary

The models within this section have outlined some of the key considerations for designing and implementing sports injury research as well as providing models for understanding injury aetiology across sports. Despite differences in the design of each of these models, there are a number of central themes throughout sports injury research. The identification of key intrinsic and extrinsic risk factors has been demonstrated as a key component in several of the models (Meeuwisse, 1994; Meeuwisse et al., 2007; Gissane et al., 2001), while it is important also to recognise how these fit within the overall ecological domain within which one is working (Hulme and Finch, 2015), which in the case of this work, is professional rugby union.

2.5 Risk factors for injury

2.5.1 Introduction

Sports injury prevention has been the subject of a large number of research articles since the late 1930s with a review of injury prevention articles in 2010 analysing over 12000 published manuscripts (Klugl et al., 2010). Of these manuscripts, the largest proportion of them was aimed at documenting aetiology (2558) followed by incidence (1354). The studies on aetiology were often aimed at trying to better understand the risk factors associated with an injury within a specific population, outlined throughout section 2.5. These risk factors can be considered as any variable that may play a role in the onset of injury and can be common across sports or specific to individual sports. These risk factors can be intrinsic or extrinsic in nature, meaning they relate to the individual athlete or the environment to which the athlete is exposed, respectively. The following section will provide an overview of some of the risk factors associated with injury risk across sports that could be considered as potential confounders in the analysis of training load and injury risk in professional rugby union.

2.5.2 Intrinsic risk factors

2.5.2.1. Age and Playing Experience

Age and playing experience are two intrinsic risk factors that have previously been cited within sports injury literature. However, the group reported as carrying the greatest risk varies from study to study, with evidence suggestive of increased risk for young, old and mid-career players, depending on the study. In professional rugby union, the highest risk has been reported in the youngest age group (<21 years) (Brooks, 2004); however, in amateur rugby union the highest risk has been reported in a 25-29 years age group (Lee, Garraway and Arneil, 2001) and in a 21-24 years age group (Chalmers, Samaranayaka, Gulliver and McNoe, 2012). Differences in study outcomes may be due to methodological inconsistencies such as the choice of reference age-group used. For instance, Lee et al. (2001) where an under 16 reference group was used for comparison with adult population, which is not appropriate given the differences between adult and youth rugby. In Australian Football League (AFL), age has been shown as a significant risk factor for specific injury types such as hamstring and calf injuries (Orchard, 2001) with players over 23 being at a higher risk than those under 23, as well as hamstring injuries alone, with increasing age being a significant risk factor (Verrall, Slavotinek, Barnes, Fon and Spriggins, 2001).

The heightened injury risk in younger players may be a consequence of an adjustment period from the youth game into the senior game. For the older group experiencing a higher risk, this may be due to the accumulated fatigue over the course of a career, as well an extensive previous injury history, which is also strongly linked with injury (as discussed in a later section). However, in research demonstrating the highest risk in middle-aged athletes (25-29: Lee et al. (2001)), it may be the superior conditioning levels and reduced accumulated fatigue in younger players that leaves them at lower risk, whilst in the older players, it may be because of 'survivor bias', whereby only the most resilient athletes manage to remain relatively injury free throughout their respective careers.

Irrespective of what age carries the smallest and largest injury risk, using age as a covariate for injury has previously been reported in elite rugby union, with Williams et al. (2017c) documenting only trivial effects on injury risk. Despite this, this study accounted only for match loads and did not account for individual training exposure, which is likely to contribute a far greater proportion of overall exposure to rugby union. The use of age as a covariate in the analysis of injury risk, therefore, may be worthwhile when also accounting for training exposure.

Previous playing experience has also been well documented in previous literature, with similar mixed results as to the number of years' experience likely to provide the lowest or highest risk of injury (Quarrie et al., 2001; Chalmers et al., 2012; Rogalski, Dawson, Heasman and Gabbett, 2013; Malone, Roe, Doran, Gabbett and Collins, 2016; Colby et al., 2017). Given that both these measures will capture an element of lifetime exposure to the sport, only age will be included in the analysis.

2.5.2.2. Physical Fitness

Physical fitness has been examined at length as a risk factor for injury, with two main characteristics being focused on, namely aerobic fitness and sprint performance. Despite the number of research articles, consensus over which players are at greater risk of injury has not been established. For both aerobic and anaerobic endurance, Quarrie et al. (2001) found that in community rugby union players, neither a high nor low amount was associated with injury, with the middle groups having the highest risk of injury. In Gaelic Football, it is suggested that poor aerobic fitness is associated with higher rates of injury (Malone et al., 2016) while in rugby league lower high-intensity intermittent running ability is associated with a higher risk of injury (Gabbett, Ullah and Finch, 2012). From a sprinting perspective, there is greater agreement on injury risk patterns, with faster and more powerful players being at greater risk of injury in both rugby union (Quarrie et al., 2001) and rugby league (Gabbett and Domrow, 2005; Gabbett et al., 2012). It has, however, been demonstrated that exposure to bouts of high-speed running (95% of maximum velocity) will lower the risk of injury in Gaelic football (Malone, Roe, Doran, Gabbett and Collins, 2017c). Overall therefore, although inconclusive, greater aerobic conditioning is suggestive of reduced risk of injury, while in sprinting, faster players are at a greater risk.

2.5.2.3. Previous Injury

One of the most commonly cited and agreed upon risk factors for injury across all sport is that of previous injury. Whether in the context of all injury and the risk of further injury or focussing on specific injury diagnoses and the likelihood of recurrence, previous injury has been shown repeatedly to be a risk factor for injury onset. In the context of previous injury research, the timeframe over which the effects of a previous injury are studied varies, with timeframes since previous injuries ranging from weeks to years. An injury in the previous season is the most commonly reported timeframe and has been associated with an increased injury risk in athletics (Jacobsson et al., 2013), soccer (Hagglund, Walden and Ekstrand, 2006) and importantly rugby union (Quarrie et al., 2001; Lee et al., 2001; Williams et al., 2017c). Quarrie et al. (2001) showed an increased risk with more recent injuries, with injuries occurring in pre-season associated with 2.4 times the risk in-season, compared with 1.6 times the risk with an injury in the previous season. The increase in risk associated with a previous injury has been demonstrated over short and long time periods. For example in AFL, previous injury within a number of weeks demonstrated an increased injury risk (Orchard, 2001), while over longer periods (preceding three years (Theisen et al., 2013)), the risk of injury was 1.6 times higher with a previous injury in that time. In a study of match load in rugby union, all previous injuries over a 7-season period were included as a covariate for injury risk, with a "very likely harmful" effect associated with previous injury (HR:1.28:(Williams et al., 2017c)). A number of studies have observed increased injury risk for athletes injured in the preceding 12 months (Chalmers et al., 2012; Malisoux, Nielsen, Urhausen and Theisen, 2015) and of particular interest to the present study (where multiple injuries may occur within a 12 month period), Chalmers et al. (2012) reported the effects of multiple injuries in the last 12 months, with one previous injury carrying an incidence rate ratio (IRR) of 1.2 and two previous injuries carrying an IRR of 1.5. While most studies report on all injuries in the previous season, some have looked specifically at injuries common in their sports. In football, for example, a hamstring, groin or knee joint injury led to a 2-3 times greater risk of sustaining an injury of the same type in the next season (Hagglund et al., 2006). In AFL a previous hamstring, quadriceps or calf injury was associated with an increased risk of sustaining a second injury of the same type (Orchard, 2001). In rugby union, Williams et al. (2017b) reported that a large proportion of recurrent injuries (42%) occurred within the first two months after returning to play, implying that greater secondary prevention initiatives are required. While previous injury has clearly been demonstrated as a risk factor for injury, there is evidence to suggest that the previous injury itself may not be causal effect on subsequent injury that it is reported to be (Hamilton, Meeuwisse, Emery, Steele and Shrier, 2011). A previous injury may represent a causal pathway to subsequent injury through incomplete healing and weakness, altered movement patterns, loss of balance or other functional/ psychological impairments but, it is also possible that previous injury represents a "non-causal marker" for subsequent injury through genetic traits, risk-taking behaviour or other injury-prone characteristics such as playing position (Hamilton et al., 2011). While establishing the causal or non-causal effect of previous injury on subsequent injury is beyond the scope of this thesis, it is important to recognise that the previous injury itself may not be causal root of further injury risk, in particular when full and adequate recovery is achieved, allowing a player to return to baseline risk prior to return from injury (Hamilton et al., 2011).

The most commonly reported injury in professional rugby union is concussion, accounting for 20% of all injuries during the 2017-18 season (Kemp et al., 2019). Given the frequency with which these injuries occur, it is important to consider the specific role these injuries play in rugby union in the occurrence of future injuries. Considering this type of injury exclusively and risk of subsequent injury, Cross et al. (2015) reported that sustaining a concussion led to a 60% rise in injury risk for the remainder of that season. This finding was consistent irrespective of the return to play time and emphasises the importance of not only examining all previous injuries as risk factors but also the need to consider concussion in isolation when examining injury risk factors in rugby union.

2.5.3 Extrinsic risk factors

2.5.3.1. Match Loads

Match loads have been shown across multiple sports to be an extrinsic risk factor for sports injury. The relative importance of match loads has grown in recent years as fixture calendars becoming increasingly saturated in an effort to meet the commercial demands of professional sport (Soligard et al., 2016). Increasing the number of fixtures within a season may well meet the commercial demands of sport, but the impact on player welfare and injury risk also needs to be considered. In soccer the issues of short recovery periods and congested fixture schedules, with more than 1 game per calendar week, has been well documented with Dupont et al. (2010) reporting a rise in match injury incidence from 19.3/ 1000 hours to 97.7/ 1000 hours during weeks with two games compared to one. Further to this, training injury incidence significantly rose from 2.5/1000 hours to 8.3/1000 hours in the same study. Under similar conditions, Dellal et al. (2015) outlined changes in overall injury risk during periods of fixture congestion in professional soccer (6 games consecutively with 3 days between each fixture), reporting no change in the overall injury incidence. However, significant differences were observed when examining training and match injuries in isolation. During these periods, match injury incidence rose significantly, while training injury incidence dropped significantly. This decrease in training incidence was attributed to the reduced intensity implemented by the coaching staff during these periods. This reduction in intensity leading to reduced injury incidence has also been shown in rugby league where Gabbett (2004a) outlined a significant relationship between training intensity and training injury incidence as well as match intensity and match injury incidence. In rugby league, the effect of between-game recovery has also been investigated with both the short (5-6 days) and long (9-10 days) turnaround periods shown to produce the highest risk (Murray, Gabbett and Chamari, 2014). However, these results must be interpreted cautiously given the small injury counts and, therefore, wide confidence intervals associated with these findings. In a study specific to professional rugby union, Williams et al. (2017c) outlined the effect of match involvements (>20 mins played) over both a chronic (12 month) and acute (4 week rolling) period. Exposure to match load over a 12-month period showed a non-linear association with injury risk, where players with less than 15 games and over 35 games were at a greater risk of injury than those with between 15 and 35 game involvements. Further to this, monthly match exposure was shown to have a linear relationship with injury risk, with an increase in 80-minute match equivalents demonstrating an increase in injury risk. These findings would suggest that in rugby union, rolling 12-month match exposure is an important factor to consider with players exhibiting higher and lower match involvements at the highest risk. It is, therefore, important to consider how match loads may interact with other key risk factors in the casual pathway to injury onset.

2.5.3.2. Sport specific injury mechanism

Irrespective of the level of play, the tackle is the event that has been repeatedly documented as the most injurious event in rugby union, being responsible for 59% of all injuries during match play (Bathgate, Best, Craig and Jamieson, 2002b). The tackle is associated with over 5 times more injuries than any other contact event, with an incidence of 33.9/1000 hours reported by Fuller et al. (2007a). In the case of a match event such as the tackle, reporting the rate of injury per unit of time may be limited, given that that changes in the rate of injury per 1000 hours could be the result of both an increased risk in a tackle situation, or an increase in the actual number of events occurring. To overcome this, propensity provides a measure of injury per 1000 events, in this case, the tackle, which shows that per 1000 tackle events in match play, 6.1 injuries occur (Fuller et al., 2007a). Given an average of 215 tackles occurring per game, this results in an average of 6.1 injuries occurring every 4.7 games, meaning that more than one tackle related injury will occur per game played (Fuller et al., 2007a). It is clear that the tackle represents the most dangerous facet of rugby union match play, with Quarrie et al. (2008) reporting that tackles from the front and side most frequently cause injury while the highest propensity of injury occurs in tackles from behind. Of particular interest in the context of modern-day rugby union, is the relationship between the tackle and concussion risk, with concussion representing the most commonly reported injury for the period 2011-12 to 2017-18 (Kemp et al., 2019). The mechanism for these injury types is most often the tackle with Cross et al. (2017) reporting an increased risk of injury associated with the tackle when the tackler is accelerating (Odds Ratio (OR): 2.49, 95% Confidence Intervals (CIs): 1.70-3.64), moving at high speed (OR: 2.64,: 95% CIs 1.92 - 3.63) or head to head contact occurred between players (OR 39.9, 95% CIs: 22.2-71.1). In the context of how preventable these injuries types may be, it is clear that there is an unpredictability to the tackle and, therefore, more targeted analysis of injuries where the mechanism may be more preventable may be useful, such as running injuries, which are consistently reported as the most common and highest burden of the training injuries (Kemp et al., 2019).

2.5.3.3. Time in Game

In rugby union match play, the time during the game when the most injuries occur is consistently reported as the second half (Bathgate et al., 2002b; Brooks et al., 2005a; Fuller, Laborde, Leather and Molloy, 2008; Fuller, Sheerin and Targett, 2013; Kemp et al., 2013). However, when broken down by quarter, there are inconsistencies as to whether the 3rd or 4th quarter is responsible for a greater number of injuries. In professional club rugby in Australia, the 3rd quarter has been reported to be responsible for 40% of all injuries (Bathgate et al., 2002b) while the 3rd quarter was also reported as the quarter with the most injuries in English professional club rugby (Kemp et al., 2013) and in rugby union overall (Williams et al., 2013). In international rugby, the incidence of injury has been reported as the highest for both the 3rd quarter (102.1/1000 hours: (Fuller et al., 2008)) and the fourth quarter (116.7/1000 hours: (Fuller et al., 2013)) in successive rugby world cups. The reason for the 3rd and 4th quarters representing the highest injury risk may be due to a number of factors, including player fatigue or a mismatch in player “freshness” as substitutions are made. While an investigation examining this is not known to have been undertaken, Brooks (2004) outlined a higher risk for starting players (114/1000 hours) compared to players who enter the game as replacements (87/1000 hours) that may indicate that player fatigue could play a role.

2.5.3.4. Position

Of the 15 players on a rugby team, each player is required to undertake a specific role for the team, with distinct differences in the activities performed by each distinct positional group. Broadly, player positions can be broken into forwards (8 players) and backs (7 players), which can be further subdivided into smaller individual groupings. Playing position has been examined as a risk factor for injury in rugby union on numerous occasions, with the majority of research reporting no difference or trivial differences between position groups, classed broadly as forwards and backs (Brooks et al., 2005a; Quarrie et al., 2001; Williams et al., 2017c; Brooks and Kemp, 2011). When divided into individual positions or smaller groupings, however, significant differences between positions are apparent. Despite these differences, the players highlighted as being at the greatest risk varies between and within studies depending on whether injury incidence, severity or burden is the measure of interest. In Brooks et al. (2005), hookers and fly-halfs were shown to have the highest injury incidence, while a right lock and open side flanker demonstrated the highest injury severity. Contrary to this, Quarrie et al. (2001) reported a significant increase in the proportion of time in season missed by midfield backs. What is clear from the research to date is that to understand differences in risk based on playing position, categorisation must extend beyond broad forward vs back groupings and must be recorded on a more specific level. By completing analysis to this level, a greater understanding of risk can be captured, and, therefore, will have a greater impact on the individual specific injury prevention programmes based on position, as called for by Brooks and Kemp (2011).

2.5.3.5. Surface Type

In recent years, there has been a proliferation in the number of artificial surfaces types being used in rugby union across different levels of the sport, with the stated benefits of these pitch types ranging from versatility, durability, multipurpose use and ease of maintenance (Drakos, Taylor, Fabricant and Haleem, 2013). The impact of these surface types on injury risk must, however, be considered given the difference between the widely used natural grass and hybrid pitch types. Despite showing no differences in the incidence of injury between surface types (Ranson, George, Rafferty, Miles and Moore, 2018; Kemp et al., 2019), both burden and injury severity appear significantly higher on artificial turf pitches, with an average of 9 days greater absence per injury on artificial turf compared to natural grass pitches (Kemp et al., 2019). Breaking injury down into smaller categories, abrasions have been reported as significantly higher on artificial turf compared to natural grass (119/1000 hours vs 15/1000 hours (Williams, Trewartha, Kemp, Michell and Stokes, 2016a)) as well as thigh haematoma, foot injuries and injuries to tackled players (Ranson et al., 2018), while concussion and chest injuries are reported as less likely on artificial turf vs grass (Ranson et al., 2018). While the majority of these injuries are associated with a low number of days absence, worryingly there is also a reported increased risk of more long-term injuries such as those to the anterior cruciate ligament (ACL) that were shown to be nearly 4 times more likely on artificial turf compared to natural grass, although this was not seen as being significant (Fuller, Clarke and Molloy, 2010). The mechanism differences for injury on differing surface types has been suggested as being affected by changes in shoe-surface interactions, while potential increases to the biomechanical torque and strain forces have also been suggested (Drakos et al., 2013). On artificial surfaces, rainfall in the previous week was shown to have unclear effects on injury risk (Williams et al., 2016a). Ground hardness has also often been studied with conflicting results, with Takemura (2007) reporting no association between ground hardness and injury, while Alsop (2005) reported the opposite, with injury more likely to occur when games were played on hard ground. With the rise in the number of these artificial pitch types, a greater understanding of how injury risk may differ between surface types is warranted and should be considered alongside factors such as the versatility, multipurpose use and ease in maintenance.

The preceding section has outlined some of the risk factors that have previously been reported in rugby union. The relative importance of each of these potential risk factors may be specific to each athlete and, therefore, within the overall analysis of training load and injury risk in rugby union, as many of these risk factors will be accounted for at the individual level to ensure any confounding effects are accounted for. While addressing all of these risk factors would be desirable, the integration of all risk factors is beyond the scope of this PhD thesis. Therefore, a specific focus will be placed on player age, player position, previous injury, previous concussion and match minutes as these data are readily available and are likely to be influenced by, or likely to influence, a player’s physical load and, therefore, their subsequent injury risk.

2.6 Training Load

2.6.1 Introduction

In the past decade there has been an increasing body of literature emerging regarding the influence of training load as a risk factor for injury in a sports setting. Training loads are prescribed to athletes with the aim of inducing physiological benefits and maximising performance, which is in contrast to match loads imposed upon athletes as a product of the competitive demands of the sport (Windt and Gabbett, 2016). The debate regarding the influence and importance of training load has grown sufficiently to warrant the need for scientific synthesis of information by way of literature reviews (Drew and Finch, 2016; Jones et al., 2017; Eckard et al., 2018), consensus statements from governing bodies (Soligard et al., 2016; Quarrie et al., 2016), and capturing the attention of the media in a rugby union context (Aylwin, 2016). Over the coming sections, training load will be discussed, as to its background, definitions, quantification, monitoring and other issues concerning its use in the context of sport.

2.6.2 Background

A relationship between training load and injury risk has previously been demonstrated in a multitude of sports and, therefore, a greater understanding of its role in injury aetiology is warranted. Building on the model outlined by Meeuwisse et al. (2007), an updated workload - injury aetiology model has been proposed to explain how load can impact upon injury aetiology (Windt and Gabbett, 2016) (Figure 2.5). The principles of this model are based on the work of Bannister et al. (1975), whose systems model seeks to gain a greater understanding of the positive and negative effects of training on physical performance. Considering an athlete as a system, whereby there is an input (the workload they are exposed to) and a subsequent output (physical performance), there are two consequences to each dose of load: fitness and fatigue. Fitness is a positive response to a training stimulus, which occurs when adequate recovery from that training is allowed. Fatigue, however, is a negative training response because it causes a reduction in performance capacity and/or tissue resilience. While each exposure is responsible for both a positive and negative impulse that declines after the completion of a session, the fatigue component decays at a much greater rate than that of fitness. While this model was intended by Bannister and colleagues to be used to assess the effects of training on physical performance, the principles of this systems model have been adapted to help understand how workloads may have influence injury risk (Windt and Gabbett, 2016) in a dynamic recursive model of repeated participation as described by Meeuwisse et al. (2007). In this workload- injury aetiology model, workload is described as having three roles in injury aetiology. The first of these is the increase exposure to the extrinsic risk factors outlined by Meeuwisse et al. (2007) and in turn a greater number of potential inciting events. The second and third roles outlined in this model, stem from the work of Banister et al., (1975) and outline the effects of fitness and fatigue on injury aetiology, where fitness once again represents the positive adaptations associated with training, which can improve modifiable risk factors such as aerobic capacity. As with the systems model, fatigue represents the negative consequences associated with training, causing a reduced capacity of modifiable risk factors such as tissue resilience.

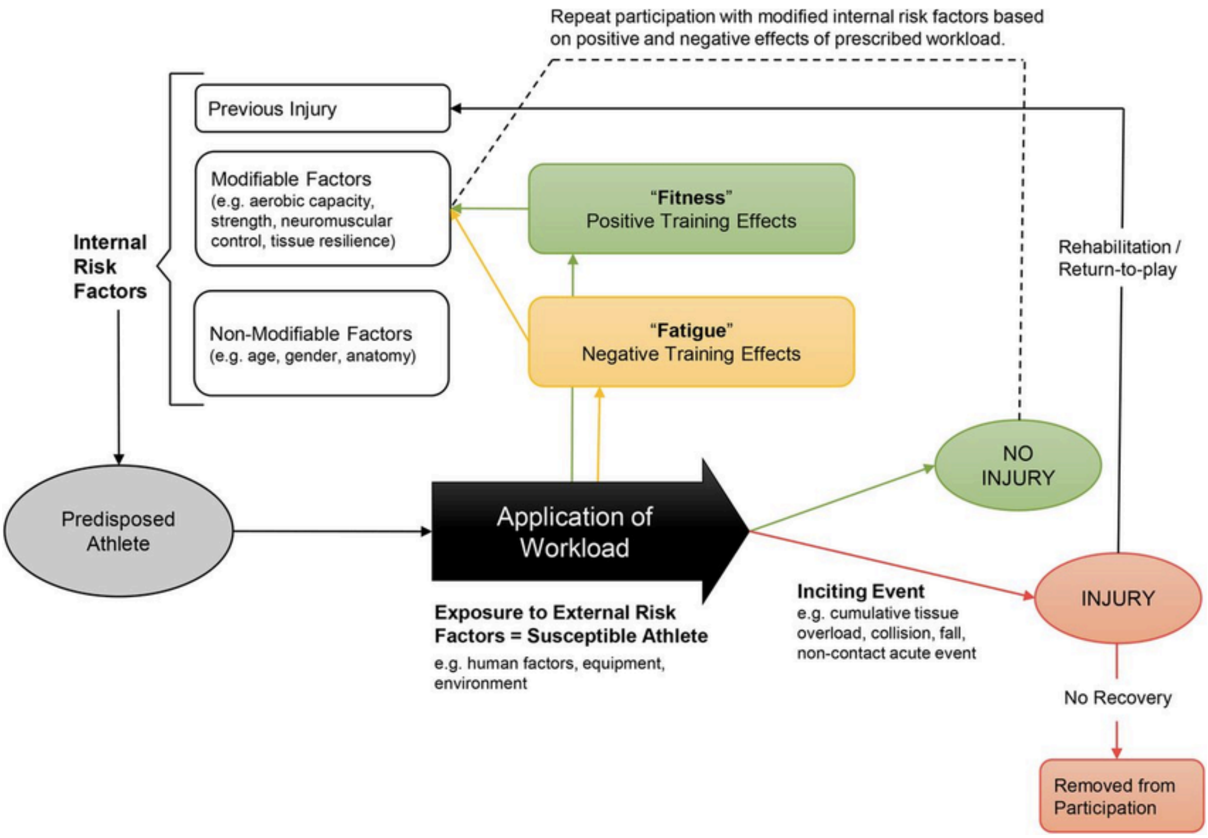

Figure 2.5: The workload-injury aetiology model (Windt and Gabbett, 2016)

While this workload - injury aetiology model demonstrates the mechanism by which a given workload may contribute to the onset of an injury, the actual relationship between these workloads and injury risk must be contextualised in the environment in which one is working. With the number of research articles examining this relationship growing exponentially in recent years, a number of systematic reviews have been undertaken to synthesise the literature (Drew and Finch, 2016; Jones et al., 2017; Eckard et al., 2018). The first of these studies examined the relationship in 35 studies of training load and injury risk, outlining at least moderate evidence for a significant relationship in 93% of the studies (Drew and Finch, 2016). Further to this, the research suggested a protective effect of training load in 31% of cases as well as a need to avoid spikes in load and manage training for up to 4 weeks after a spike. Of the 68 papers included in Jones et al, (2017), 45 examined the relationship between training load and injury risk exclusively, while a further 6 also measured illness. Similarly, this study concluded that an increase in risk was apparent during times of training intensification or accumulation. One of the limitations of research in this area noted by the authors was that of discrepancies between definitions in studies in areas, such as training load, fatigue, injury and illness. The final and most recent review (Eckard et al., 2018) aimed include any new evidence in the area which would be without this limitation given the publication of a consensus paper to address this limitation (Soligard et al., 2016). Of the 57 studies included, 47 showed at least partially significant results, emphasising the link between training load and injury. The evidence within this review reported subjective internal training load to be the tool with the strongest relationship with injury risk, while the use of an acute:chronic workload ratio to analyse training load data was also strongly linked.

While it is clear that there is evidence for training load as a risk factor for injury, one notable feature is how the nature of the relationship, the tools used, and the strength of the relationship is often dependent and specific to each sport and, in some cases, each individual. Of the research articles included in reviews, in both Drew and Finch (2016) and Jones et al. (2017) just two were conducted into rugby union, while Eckard et al. (2018) did not distinguish between rugby codes. Of these two studies, one used training volume (in hours) as a measure of load to assess corresponding injury risk (Brooks et al., 2008) while the second used in season session Rating of Perceived Exertion (sRPE)(Cross et al., 2016b). In both studies, a relationship between training load and injury was seen, with Brooks et al. (2008) reporting no change in incidence of injury, but significant changes in injury severity with higher training volumes, while Cross et al., (2016b) reported a relationship when considering high one week loads, large week-to-week changes in load and 4-week cumulative loads. While these studies indicate a relationship exists between training load and injury risk, given the comparatively small amount of information specific to rugby union compared with other sports, the need for a more extensive study is warranted.

2.6.3 Principles of training

Training refers to the process of applying stressors to the body with the goal of improving physical capacity and, subsequently, sporting performance (Meeusen et al., 2013; Morgans, Orme, Anderson and Drust, 2014; Morton, 1997; Soligard et al., 2016). For training prescription to be successful, an element of overload is required; however, this must be achieved in balance with adequate recovery time between successive stimuli (Meeusen et al., 2013). As a consequence of each training exposure, the response of the body can be explained as a three-stage process composed of the alarm stage, resistance stage and exhaustion (Selye, 1956). The alarm phase is the initial phase after exposure to a physical stimulus and is characterised by a decrease in system resistance in response to the stressor, whereby excessive soreness/ stiffness and a temporary decrement in performance may be seen for a period of days. Following this is the resistance stage during which the body adapts to the stimulus and returns to the body to homeostasis. This period may leave the body in a period of adaptation greater than initial levels, which is also known as supercompensation. Finally, should the body be provided with insufficient recovery time between exposure to stressors, meaning the adaptive capacity of the tissues is compromised, exhaustion can occur causing prolonged periods of fatigue and in some cases underperformance. To avoid such a scenario, the balance between overload and recovery must be carefully managed to achieve a process described as functional overreaching whereby adaptation leads to long term improvement in performance capacity (Meeusen et al., 2013). However, if this balance is not struck and recovery is inadequate or training stimulus too high, an athlete may experience a prolonged period of non-functional overreaching and eventually overtraining syndrome, which is characterised by extended periods of fatigue and decrements in performance (Meeusen et al., 2013). While overtraining syndrome is a well-established concept, whether the same prolonged overreaching mechanisms occur in rugby union is unknown. While periods of intensive competition in rugby union may contribute to general player fatigue, it is difficult to establish whether these in turn lead to the performance decrements associated with overtraining syndrome as key performance parameters in rugby union are complex, with so many elements contributing to performance. Due to the complex physical demands of rugby union, a multi-component training programme is needed to develop all of the required attributes for participation. Periodisation is a commonly used strategy to plan training cycles that can address all of the components required for sports specific preparation. It has been defined as a theoretical model that offers a framework for the planning and variation in athlete training prescription (Morgans et al., 2014). The use of these periodised plans is aimed at maximising training stimulus to allow for peaking at the correct times while allowing sufficient recovery to prevent the negative consequences of overload at potentially crucial times. These periodised plans are the basis of individual training load prescription and although in the context of this work are not controlled by the research, they must be recognised as potentially varying between different club environments.

2.6.4 Defining load

The terms “load” and “workload” are commonly used across sports science disciplines and often vary between different sports. The use of the term “load” has been the subject of widespread inconsistency in definition in the literature making comparison between studies difficult (Jones et al., 2017; Eckard et al., 2018). One of the key inconsistencies surrounds whether the term relates to the external stressors applied to an individual or whether the term relates to the psychophysiological responses to that load (Impellizzeri, Marcora and Coutts, 2019a). Given the inconsistency in reporting of load as a measure, as well as the recent emergence of load management as a major risk factor for injury, a consensus statement on load and injury risk in sport was produced by the International Olympic Committee (Soligard et al., 2016). In this statement, “load” in the context of sports medicine and exercise physiology was defined as “the sport and non-sport burden (single or multiple physiological, psychological or mechanical stressors) as a stimulus that is applied to a human biological system (including subcellular elements, a single cell, tissues, one or multiple organ systems, or the individual)". In the context of rugby union, load is recognised as multi-modal with a range of loads acting upon an athlete at any point in time including physical, psychological, social, travel, and nutritional loads, the sum of which can be described as "load" or "the total stressors and demands applied to the players" (Quarrie et al., 2016). In this PhD thesis, the loads being examined are physical loads, namely matches and training, with a particular emphasis on training, which is made up of the manipulation of intensity, duration and frequency (Smith, 2003). The specific definition of load for the purposes of this work is "the cumulative amount of stress placed on an individual from multiple training sessions and games over a period of time" as per the work of Gabbett et al., (2014). This definition of load provides a clear outline to readers as to what exactly is considered by the term load in that study. An extension of this definition pertains to load being measured as either external loads imposed upon an athlete or the internal response of that athlete to the external load (Impellizzeri, Rampinini and Marcora, 2005; Gabbett et al., 2014; Halson, 2014; Soligard et al., 2016). The external load can be described as the stimulus applied to each athlete that is measured independently of their internal characteristics (Soligard et al., 2016) or as the work completed by each athlete (e.g. 400 watts for 30 mins by a cyclist) (Halson, 2014). Measures of external load are specific to the nature of the training undertaken (resistance, distance, speed) and are prescribed by the coach to elicit a desired psychophysiological response from the athlete, which is known as the internal load (Impellizzeri et al., 2019a). This relative physiological and psychological stress imposed can be used to identify individual player response and subsequent adaptation to the external load (e.g. heart rate) (Halson, 2014). In managing an athlete's load, a measure of both internal and external load is preferable to allow for an understanding of both the work undertaken and the individual response. This is important as two athletes may be prescribed the same external load, however the internal load of those two athletes may differ substantially. In circumstances where both internal and external load cannot be captured, internal load has been recommended as the primary measure for monitoring athletes as it represents a better determinant of training outcome (Impellizzeri et al., 2019a). For the purpose of this thesis, load is defined as in Gabbett et al. (2014) because it pertains to the cumulative physical load imposed by matches and training over a period of time.

2.6.5 Quantifying Load

To capture the load of an athlete, a wide variety of methods have been proposed. Each method will differ in the type, nature, amount, quality and specificity of the data it supplies to a sport scientist and some key considerations for this must be made. In a 2017 consensus statement on monitoring athlete training loads, several of the challenges and considerations with this process were outlined such as the resources available, expense, reliability, validity, precision, ease of use, standard of competition and staffing required to collect and use the data (Bourdon et al., 2017). Given the number of session types and players associated with team sports, choosing an appropriate tool can be challenging. However, appropriate load monitoring may assist not only in the management of injury risk but may also provide a scientific explanation for changes in performance (Halson, 2014). Further to this, with proper use and coach and player buy-in, a load monitoring tool can provide additional benefits to both communication and relationship building between players, coaching and support staff (Halson, 2014).

Measures used to quantify training load can be either external or internal. Measures of external load include power output, time motion analysis, global positioning systems (GPS) data and accelerometer data, while measures of internal load include heart rate, blood lactate, oxygen consumption and rating of perceived exertion (Halson, 2014). Despite the widespread use of tools and mechanisms for measuring training load, there is still no definitive single marker currently used within the research literature (Halson, 2014). The following section will outline the main strengths and weaknesses of the markers used in the current thesis. An overview of some of the other methods used in existing literature can be seen in Figure 2.6, which outlines the cost, equipment needed, ease of use, validity, reliability, utility and output associated with each load monitoring type (Bourdon et al., 2017).

Method	Cost	Hardware needed	Software needed	Ease of use	Valid	Reliable	Used to interpret	Used to prescribe	Variables
Internal Measures									
RPE	L	N	Y/N	H	M–H	M–H	Y	Y	Single variable in AU (time dependent)
Session rating of perceived exertion	L	N	Y/N	H	M–H	M–H	Y	Y	Single variable in AU (time dependent)
TRIMP[4]	L–M	Y	Y	M	M–H	M–H	Y	N	Single variable in AU (time dependent)
Wellness questionnaires*	L	N	Y/N	M–H	M	M–H	Y	Y/N	Ratings, checklists, AU scale measures
Psychological inventories (eg, POMS, Rest-Q-Sport)*	L–M	N	Y/N	M–H	M–H	M–H	Y	Y	Ratings, checklists, AU scale measures
Heart-rate indices	L–M	Y	Y	H	H	M–H	Y	Y	Heart rate, time in zones, HR variability/recovery measures, etc
Oxygen uptake	H	Y	Y	L	H	H	Y	Y	VO_2, metabolic equivalents
Blood lactate	M	Y	Y/N	M	H	H	Y	Y	Concentration
Biochemical/hematological assessments	M–H	Y	Y/N	L	H	M–H	Y	Y	Concentrations, volumes
External Measures									
Time	L	Y	Y/N	H	H	H	Y	Y	Units of time (s, min, h, d, wk, y)
Training frequency	L	N	N	H	H	H	Y	Y	Session count
Distance/mileage	L	Y/N	Y/N	H	H	H	Y	Y	Units of distance (m, km)
Movement repetition counts	L	Y/N	Y/N	M–H	H	M–H	Y	Y	Activity counts (eg, steps, jumps, throws)
Training mode	L	Y/N	N	H	H	H	Y	Y	Weight training, run, cycle, swim, row, etc
Power output	M–H	Y	Y	L–M	H	H	Y	Y	Relative (W/kg) and absolute power (W)
Speed	L–M	Y	Y/N	M–H	H	H	Y	Y	Speed measures (m/s, m/min, km/h)
Acceleration	L–M	Y	Y	L	H	H	Y	Y	Acceleration measures (m/s^2)
Functional neuromuscular tests	L–M	Y	Y/N	M	M–H	H	Y	Y	Countermovement-jump and drop-jump measures
Acute:chronic-workload ratio	L–M	Y/N	Y	M	M–H	M–H	Y	Y	Size of acute training load relative to chronic load
GPS measures	M	Y	Y	M	M–H	M	Y	Y	Velocity, distance, acceleration, time in zones, location
Metabolic power	M	Y	Y	L–M	L–M	M	Y	N	Energy equivalent
Time–motion analysis video (automated)	H	Y	Y	L	M–H	M	Y	Y	Velocity, location, acceleration
Time–motion analysis video (nonautomated)	M–H	Y	Y	L	M–H	M	Y	Y	Velocity, location, acceleration
Accelerometry	M	Y	Y	L–M	M–H	M	Y	N	*x-y-z g* force
Player load	M	Y	Y	M	M	M	Y	Y	Single variable in AU (time dependent)

Abbreviations: L, low; M, medium; H, high; Y, yes; N, no; AU, arbitrary units.
*Measures of training response.

Figure 2.6: Summary of training load monitoring methods (Bourdon et al., 2017)

2.6.6. Measuring internal training load

To assess the relative stress placed on an athlete in response to external training stimuli, the internal load or response can be captured from a physiological or psychological perspective. These measures can be either objective (e.g. heart rate or lactate) or subjective (e.g. wellbeing or perceived exertion) (Halson, 2014). To measure internal load objectively, a measure such as heart rate can be used and despite it being one simple measure, it can produce a number of complex indices (Buchheit, 2014). Heart rate can be measured at multiple times (including during sleep, at rest, during exercise and following exercise) to provide simple absolute measures of heart rate or more complex values such as heart rate variability or heart rate reserve (Buchheit, 2014; Borresen and Lambert, 2009). Monitoring of heart rate is particularly useful as a measure of intensity as it represents a linear relationship with steady state work rate and is individual to each player, therefore allowing for within-person variation (Borresen and Lambert, 2009). As a monitoring tool for load, a number of methods have been proposed in the analysis of heart rate including Banister's (1991) and Edwards' (1993) TRIMP (TRaining IMPulse) (Impellizzeri et al., 2005). These methods combine the intensity and duration of a session to produce a single term to define load in that specific session (Impellizzeri et al., 2005). Banister's model utilises percentage of heart rate reserve as a measure of intensity, while Edwards uses the accumulated time in each of the five heart rate zones from 50-60% of heart rate maximum to 90-100%.

Measuring the internal response to load subjectively can be undertaken in a number of ways with one commonly used tool being that of wellbeing. A number of questionnaires have been developed and validated in a sports setting to assess wellbeing in athletes including the Profile of Mood States (POMS) (McNair, Lorr and Droppleman, 1971), Daily Analysis of Life Demands for Athletes (DALDA) (Rushall, 1987) and the Recovery-Stress Questionnaire for athletes (REST-Q) (Kellmann and Kallus, 2001). Each of these questionnaires is designed to assess different components of wellness with the POMS targeting mood (including anger, confusion, depression, fatigue, tension and vigour), the REST-Q targeting the frequency of stress and recovery activities and DALDA assessing stress and the factors associated with a stressed athlete (e.g. diet, home life, work etc.). Each measure is recorded intermittently over time and is targeted at subjectively assessing athlete wellbeing using a 5-point Likert scale (POMS), 7-point Likert scale (REST-Q) and a 3-point, "worse than normal"/ "normal"/ "better than normal" scale (DALDA). Both wellness questionnaires and heart rate offer useful tools to collect internal load for an athlete; however, for the purposes of this study, the session rating of perceived exertion method of training load data collection was used, as outlined below.

Session rating of perceived exertion (sRPE) is a simple, reliable and non-invasive method of capturing internal training load for athletes (Comyns and Flanagan, 2013). sRPE is captured using both a measure of session intensity (captured using a modified Borg (1987) scale) and session duration. This method of capturing training load was first proposed by Foster (1998) and is designed to provide the user with a single number to represent the magnitude of a session. At the end of a training session, an athlete is asked to rate the session's intensity on a category ratio 10 (CR-10) point scale that goes from "Rest" at the lower end to "Maximal" at the upper end (Figure 2.7), this is known as a session RPE. This value is then multiplied by the session's duration (in minutes) to produce a single load score for that specific session, described as sRPE TRIMP (abbreviated to sRPE throughout) (Foster, 1998). One of the key strengths to the sRPE method is its applicability to multiple different session types, with the tool being shown as reliable in steady-state aerobic training (Foster et al., 2001), intermittent-aerobic training (Foster et al., 2001) and strength training (Day, McGuigan, Brice and Foster, 2004; Comyns and Flanagan, 2013). In addition to being reliable, the tool has been shown as comparable to other measures of internal load including heart rate ($r = 0.89$) (Gabbett and Domrow, 2007), TRIMP ($r = 0.65$-0.91) (Clarke, Farthing, Norris, Arnold and Lanovaz, 2013), Edwards' TRIMP ($r = 0.69$-0.91)(Clarke et al., 2013) and lactate ($r = 0.86$) (Gabbett and Domrow, 2007). In a recent systematic review, the validity and reliability of the measure was confirmed in multiple sports and physical activity types including basketball, resistance training, soccer, swimming, taekwondo, diving and rugby (Haddad, Stylianides, Djaoui, Dellal and Chamari, 2017).

Originally, the perceived exertion using the CR-10 was designed to be completed 30 minutes after the cessation of exercise, to ensure that a measure of the global intensity of the session was provided and that the score was not influenced by the session ending with a particularly easy or difficult component (Foster et al., 2001). More recently, numerous time periods have been documented with 10 mins after exercise (Uchida et al., 2014), 15 mins after exercise (Kraft, 2014) and 30 minutes all used (Clarke et al., 2013). Further to this, Christen et al. (2016) examined the temporal robustness of the measure, concluding that no significant differences existed when collecting the RPE score at time points from 5 mins to 24 hours post exercise. Another methodological factor to consider is the blinding of athletes to one another's responses, with Comyns and Hannon (2018) outlining the potential for athletes to falsify RPE values should they see an opportunity to gain selection ahead of other teammates. To avoid such bias being introduced, players should be educated to the purpose and utility of the sRPE measure as well as blinded to the scores of other athletes, which can be done using mobile phone applications or verbally with the player in an isolated setting (Comyns and Hannon, 2018).

While sRPE can be implemented in multiple sports, consideration must be given to the factors that can affect a player's RPE. These factors are outlined as personality of the athlete, gender, age, fitness, expertise as well as more environmental factors including music, feedback, diet, temperature, attitude and scale variation (Haddad et al., 2017). Despite the generalisability of many factors across all sports, it must also be considered that factors affecting sRPE can also be sport-specific, with Malone et al. (2017a) demonstrating that players with less experience (0-1 years) report higher average sRPE values compared with more experienced (2-3, 4-6, 7+ years) players, while players with slower 1 km time trial scores also reported higher values. Furthermore, within each sport, sRPE can be compared with other measures of training load to identify the similarities between measurement tools across different sessions types (Lovell, Sirotic, Impellizzeri and Coutts, 2013). For example, Lovell et al. (2013) demonstrated a strong correlation between sRPE and total distance (derived from GPS) in skills conditioning sessions (0.88), however, a range of values were reported depending on the session type and nature of the training being undertaken (0.39: "wrestling"- 0.88 "Skills conditioning"). Despite the widespread use of sRPE as a useful global measure of training load, it could be argued that the measure is too simple to capture the different exertion components experienced during training (McLaren, Smith, Spears and Weston, 2017). To overcome this, the use of differential RPE scores have been suggested to isolate specific perceptual demands in different training modalities (Weston, 2013; McLaren et al., 2017). These differential RPE scores can be broken down into sRPE-B (breathlessness), sRPE-L (leg muscle exertion), sRPE-U (upper body exertion), sRPE-T (cognitive technical demands). While this may represent a more detailed quantification of internal load, it must be recognised that this extended grouping increases the number of sRPE values from one to four, meaning a greater number of data points has to be collected and analysed as well as increasing the requirements from each individual athlete, whereas one single sRPE measure may provide an adequate measure of global load. In professional rugby union, sRPE is collected by a large number of clubs, with 19 of 20 reporting the use of this tool (Comyns and Hannon, 2018). Of those coaches who used the tool, the methods in which it was collected varied between teams, with 41% indicating they took RPE scores immediately after training, 53% reporting 15 minutes after training and 6% reporting 30 minutes after training. In total, 89% of clubs captured the data verbally while 11% used a mobile application. When asked about their use of the tool, 80% found sRPE to be a valid method of collecting training load data while 63% of coaches agreed that it helped to prevent injury and 61% agreed that it helped to enhance performance. It is clear from this work that sRPE is a widely used and effective tool for capturing training load in professional rugby union and can offer utility in the management of preventing illness and injury as well as enhancing performance (Comyns and Hannon, 2018).

A recent review on managing load in rugby union recommended that measuring load at a professional level should incorporate sRPE (Quarrie et al., 2016). Additionally, two recent reviews of training load and injury risk supported the use of sRPE, with Drew and Finch (2016) recommending that sRPE be used in future prospective studies of injury, while Eckard et al. (2018) suggested that the link between training load and injury risk was strongest in subjective internal training load data. In the population of interest in this thesis, Cross et al., (2016b) demonstrated the utility of sRPE training load data to examine the risk of injury across multiple teams at once and, therefore, provided justification for the continued use of the tool in the current work, where 12 teams per season will be examined.

Rating	**Descriptor**
0	**Rest**
1	**Very, Very Easy**
2	**Easy**
3	**Moderate**
4	**Somewhat Hard**
5	**Hard**
6	**.**
7	**Very Hard**
8	**.**
9	**.**
10	**Maximal**

Figure 2.7: The modified Borg scale used in the collection of sRPE (Borg et al., 1987; Foster et al., 2001).

2.6.7 External training load

External load is the main determinant of internal load and has been described as the work completed by an athlete (Impellizzeri et al., 2005; Halson, 2014). As with internal load, external load can be quantified via a number of different measures, including: time, power, GPS, time motion analysis and counts of events e.g. throws, jumps, tackles (Bourdon et al., 2017). As with all measurement tools, each will be associated with a number of strengths and weaknesses, meaning that the most applicable tool must be chosen for the setting within which it is to be implemented. A simple and accurate, yet time consuming method of collecting external training load is that of event counting (Dennis, Farhart, Goumas and Orchard, 2003). Event counts have been undertaken in the analysis of injury risk in multiple sports including cricket (Dennis et al., 2003; Hulin et al., 2014) and baseball (Lyman et al., 2001). Analyses such as these can allow for the identification of thresholds for injury risk increases should they be surpassed. For example, Dennis et al. (2003) reported that players completing less than 123 deliveries and greater than 188 deliveries per week in cricket were at a greater risk of injury than those who bowled between 123 and 188 deliveries per week (Relative Risk (RR): 1.4). In baseball, throwing greater than 75 pitches in a game was associated with an increased risk of injury compared with 1-24 pitches (OR: 1.56, 95% CIs: 0.89-2.75) (Lyman, Fleisig, Andrews and Osinski, 2002). More recently, Hulin et al. (2014) reported that a training stress balance (average number of balls in the past week/ average number of balls in the past 4 weeks) of greater than 200% associated with a significant rise in injury risk in cricketers (RR: 3.3, 95% CIs: 1.5-7.25). The methods associated with this type of monitoring often involve a lengthy process of observation by researchers using video analysis; however, more time efficient methods, such as ball/pitch count books have also been employed (Dennis et al., 2003; Lyman et al., 2001). While the use of counts may be useful in the context of rugby union to capture events, such as tackles and scrums, other monitoring tools have been favoured recently with emphasis being put on GPS systems to collect measures of athlete external load as well as some contact demands.

2.6.8 Global Positioning Systems (GPS)

The use of GPS in elite rugby union has grown exponentially in recent years, with a rapid uptake in the technology (Aughey, 2011). Until the introduction of the first commercially available GPS systems for sport in the early 2000s, analysis of movement on the field of play was captured using the more manual time motion analysis (TMA) systems that allowed for the observation of distance, intensity and extent of discrete activities in match play (Reilly and Thomas, 1976). The introduction of GPS technology has revolutionised the way in which data is captured but also our knowledge regarding player movement in sport (Aughey, 2011). GPS technology works using radio signals from satellites to GPS receivers on earth, with a minimum of 4 satellites required for the accurate triangulation of the location of the receiver (Aughey, 2011). Once the position of a receiver is known, the displacement of the receiver can be measured over time to calculate the distance and velocity of the unit (Aughey, 2011). Originally used for military purposes, the first validation study of a GPS system was undertaken in 1997, while the first commercially available units for sport were produced in 2003 (Aughey, 2011). Arguably, one of the most difficult topics in relation to the use of GPS units is the validity of the systems, with a number of studies and reviews having been undertaken in the last decade (Aughey, 2011; Varley, Fairweather and Aughey, 2012; Boyd, Ball and Aughey, 2013; Cummins, Orr, O'Connor and West, 2013; Buchheit et al., 2014; Scott, Scott and Kelly, 2016; Buchheit and Simpson, 2017). As the technology has developed, the validity and reliability of GPS units has also improved; however, some common themes exist between these reviews. In general, the greater the sampling frequency of the GPS unit, the more accurate and valid the unit becomes (Aughey, 2011; Varley et al., 2012), up to 15 Hz, after which no additional benefit appears to exist (Scott et al., 2016). The accuracy and reliability of these GPS systems appear to be affected to a greater extent during high speed activities, short movements and in particular movements with a significant number of directional changes (Aughey, 2011; Varley et al., 2012; Boyd et al., 2013). The integration of triaxial accelerometers into modern GPS systems (that sample at a far greater rate than a GPS unit alone) has allowed for the improved quantification of these shorter faster movements as well as measuring new metrics such as player/ body load, forces acting on the athlete and contact of athlete with surfaces, objects and other athletes (Scott et al., 2016). More specifically, in the context of collision-based sports, Howe et al. (2017) have highlighted the usefulness of the additional information provided by accelerometers in the physical preparation and monitoring of athletes in these sports. The use of these tools to capture the external load and locomotor demands of training and match play has progressed the management of training load at a team level as well as assisting in the decision making on individual player programmes to increase performance and minimise injury risk (Buchheit and Simpson, 2017). The use of GPS technology requires the selection of the appropriate metrics that are specific and relevant to the sport being monitored. Buchheit and Simpson (2017) have categorised these metrics into three levels:

- Level 1: Distance in speed bands
- Level 2: Events related to change of velocity (e.g. accelerations, decelerations and change in direction)
- Level 3: Events derived from inertial sensors/ accelerometers (e.g. impacts, PlayerLoad)

Buchheit and Simpson (2017) identified potential uses of specific GPS metrics, with total distance commonly used as a measure of overall training volume, whereas metrics such as high speed running, accelerations and decelerations may be more important for managing individual injury risk, given the greater influence on neuromuscular-orientated load (Buchheit and Simpson, 2017). This is further supported by a recent study that demonstrated that impacts over 3G and high intensity running variables cause the greatest increase in Creatine Kinase (biomarker of muscle damage) levels post-match (Gastin, Hunkin, Fahrner and Robertson, 2019). The use of GPS technology has been applied in a variety of sports including Australian football, soccer, rugby union, rugby league, cricket, hockey, lacrosse and netball. However, with the exception of cricket, there is a clear lack of standardisation in the definition of speed zones between and within sports (Cummins et al., 2013). Given this, comparison between sports is often difficult and while consensus would be useful and desirable for comparison sake, it is difficult given the disparity in work rate patterns associated with each sport (Cummins et al., 2013). In the context of rugby union specifically, a number of studies have examined the match demands of the sport using GPS technology (Cunniffe et al., 2009; Suarez-Arrones, Portillo, Gonzalez-Rave, Munoz and Sanchez, 2012; Quarrie et al., 2013) while some have focused more specifically on impacts only (Venter and Opperman, 2011). More recently, these average match demand studies have been built upon by the identification of "worst case scenarios" for match play, which represent the toughest periods of the game, rather than the average demands (Reardon et al., 2017; Cunningham et al., 2018). These types of analyses can then be used for the purposes of training prescription to ensure the athletes are prepared for the most demanding passages of match play. While the use of GPS technology for monitoring athletes is rising, it is with care that one uses these tools, given the potential for high inter-unit differences in results (Buchheit et al., 2014). Furthermore, Buchheit and Simpson (2017) outline the need for quality data collection, understanding of limitations and quality of data analysis, reporting and utilisation for the successful use of GPS in the context of team sports monitoring.

2.6.9 Using load data

2.6.9.1 Overview

After the selection of an appropriate measure, there are a number of considerations that must be accounted for with regard to the analysis of the data. The first consideration discussed is the method used to aggregate data, with a number of possibilities available. Examples of the measures used to aggregate and analyse training load data include acute loads, chronic loads, acute:chronic ratio, training strain, training monotony and week-to-week changes. This section will provide a brief overview of each of these and will include information regarding the origin of each measure, how it is calculated and current knowledge surrounding its association with injury risk.

2.6.9.2 Acute load

In the context of training load management, the acute load of an athlete can be seen as analogous to the fatigue status of an athlete (Banister et al., 1975; Gabbett, 2016a). An acute load, therefore, can be considered as a timeframe within which fatigue can occur. This timeframe can be as short as one single session to multiple days or weeks, with one week seeming a logical and convenient unit of measurement for many settings (Gabbett, 2016a). Despite this 7-day measurement being commonly used across multiple sports and research studies (Rogalski et al., 2013; Hulin et al., 2014; Colby, Dawson, Heasman, Rogalski and Gabbett, 2014; Cross et al., 2016b; Bowen, Gross, Gimpel and Li, 2017; Murray, Gabbett, Townshend, Hulin and McLellan, 2017b; Thornton, Delaney, Duthie and Dascombe, 2017), there are a number of studies examining different acute periods including 14 day periods (Stares et al., 2018) as well as an assessment of 2-9 day acute time periods (Carey et al., 2017a). Irrespective of the time period used to calculate acute load, there is evidence to suggest that there is a positive relationship between acute load and injury risk in Australian football (Piggott, Newton and McGuigan, 2009; Rogalski et al., 2013; Murray et al., 2017b; Esmaeili et al., 2018), Cricket (Orchard, James, Portus, Kountouris and Dennis, 2009; Hulin et al., 2014; Orchard et al., 2015), Basketball (Anderson, Triplett-McBride, Foster, Doberstein and Brice, 2003), Football (Bowen et al., 2017) and Gaelic football (Malone et al.,

2016) among others. Across the rugby codes, a similar relationship is well documented in rugby league (Gabbett, 2004b; Gabbett and Domrow, 2007; Gabbett and Jenkins, 2011) and, to a lesser extent, rugby union (Cross et al., 2016b). In contrast to this, there are several studies showing no relationship between acute loads and injury risk in Australian football (Colby et al., 2014; Colby et al., 2017), rugby league (Killen, Gabbett and Jenkins, 2010) and rugby union (Brooks et al., 2008). While the evidence supporting the association between acute spikes and increased injury risk is unclear, given that training loads are a modifiable injury risk factor, a greater understanding of how acute spikes may influence injury risk in a rugby union setting is warranted.

2.6.9.3 Chronic load

Where acute load is considered conceptually analogous to the fatigue status of an athlete, chronic load can be considered analogous to the fitness status of an athlete (Banister et al., 1975; Gabbett, 2016a). As with acute load, there has been a number of chronic time periods suggested for measurement of chronic load, with 4 weeks being the most commonly used. Aside from 4 weeks, others have examined the effect of differing time frames including 15, 20, 25, 30 and 35-day time windows (Carey et al., 2017a); 14, 21, 28, 35, 42, 49 and 56-day time windows (Stares et al., 2018) and in rugby union specifically 14, 21 and 28-day time windows (Cross et al., 2016b). Having chosen a time window to capture chronic load, the data aggregation method must also be chosen whereby the data can be summed over time or averaged. Further detail surrounding the methods for this step are provided in section 2.7.9.3.

The relationship between chronic load and injury risk is somewhat similar to that of acute load, whereby both a positive and negative relationship has been described. In the majority of cases, a medium to high chronic load has been reported as protective against injury, both in isolation as well as combined with other workload parameters. In Australian football, low chronic loads have been associated with an increase in injury risk (Stares et al., 2018) with Colby et al. (2017) highlighting the important moderating role played by chronic loads in the workload- injury relationship. Similar findings have been reported in soccer (Malone et al., 2018) and Gaelic football (Malone et al., 2017c) while in rugby league a number of studies has demonstrated the importance of building a chronic load to improve player resilience to injury (Hulin, Gabbett, Caputi, Lawson and Sampson, 2016a; Hulin, Gabbett, Lawson, Caputi and Sampson, 2016b; Windt, Gabbett, Ferris and Khan, 2016). In contrast to this, studies conducted in Australian football have also shown an increased risk of injury with high 2-week chronic loads (Rogalski et al., 2013), high 3-week cumulative total distance and sprint distance (Colby et al., 2014) and high overall chronic loads (Esmaeili et al., 2018), which interestingly were of greater importance when previous injury was accounted for. Further to this, mixed results were found in soccer whereby a higher accumulated load was associated with higher injury risk, yet the authors suggested that if chronic load could be achieved through a progressive increase in chronic loads, they may help to develop resilience to higher acute loads and injury risk (Bowen et al., 2017).

In the context of rugby union, only one study has examined the effect of chronic training loads on injury risk with Cross et al., (2016b) demonstrating the likely beneficial reduction in injury risk when intermediate 4-week cumulative loads (5932-8651 arbitrary sRPE units) were achieved by players, compared with a reference value of less than 3684 arbitrary units (OR: 1.39, 95% CI: 0.98-1.98). As can be said of acute load, the evidence surrounding chronic loads and injury risk is unclear. Therefore, to validate the work of Cross et al. (2016b) in elite rugby union, these loads should be included in the modelling process throughout this thesis.

2.6.9.4 The acute:chronic workload ratio

The concept of acute load as analogous to fatigue and chronic load as analogous to fitness stems from the work of Eric Banister and colleagues in 1975 in the context of modelling performance (Banister et al., 1975). The systems model outlined how swimming performance was the product of the difference between a positive fitness function and a negative fatigue function, with decay time constants for fitness and fatigue set at 50 and 15 days, respectively. While the original use of the fitness-fatigue model was designed for performance, more recently this has been applied in the context of injury risk, using the acute:chronic workload ratio (Gabbett, 2016a) [formerly training stress balance (Hulin et al., 2014)]. This use for the fitness-fatigue model was proposed by Hulin et al. (2014) as the training stress balance, calculated as the acute load divided by chronic load, and expressed as a percentage. In this study, conducted with fast bowlers in cricket, training load was measured using both external load (number of balls bowled) as well as internal load (sRPE), with acute loads represented by 1 week loads and chronic loads represented by a rolling 4-week average. As the first study to use this model for injury risk management, the study highlighted the increased risk of injury when acute load becomes higher than the chronic load, leading to training stress balance scores greater than 100%. In particular, training stress balance values of greater than 200% demonstrated a relative risk of 3.3 (95% CIs: 1.5-7.25). Following this initial work using fitness and fatigue training loads to establish an athlete's training stress balance, the concept was renamed and soon popularised as the "acute:chronic workload ratio" (Gabbett, 2016a). In this paper, Gabbett outlines the potential for the acute:chronic workload ratio to act as a measure for managing player fatigue with the aim of minimising injury risk, outlining a ratio sweet spot of 0.8-1.3, with spikes of greater than 1.5 associated with increases in injury risk (Gabbett, 2016a). The so-called "sweet spot" outlined by Gabbett of between 0.8 and 1.3 was selected based on evidence suggesting that too little training will leave an athlete unprepared for the requirements of the sport's participation, while too much training may induce unwanted fatigue or excessive loading of tissues and, therefore, an increased injury risk. This concept of too much and too little training was associated with injury risk; however, it has been previously documented by multiple authors including Dennis et al. (2003), Orchard (2012) and Gamble (2013). The identification of the 0.8 to 1.3 range specifically as the acute:chronic sweet spot stems from the work of Blanch and Gabbett (2016), who demonstrated a strong polynomial relationship (R^2= 0.53) between the acute:chronic ratio and injury likelihood in cricket, rugby league and Australian football. Based on the fit of this curve, Blanch and Gabbett go on to outline the potential utility of the acute:chronic ratio in returning players to sport after injury with injury likelihoods reported based on the acute and chronic loads of the athlete.

With respect to the calculation of the acute:chronic workload ratio, the most common method of calculation uses 1 week acute loads and 4 week rolling averages (Blanch and Gabbett, 2016; Hulin et al., 2016a; Hulin et al., 2016b; Malone et al., 2016; Malone et al., 2017b; Bowen et al., 2017; Colby et al., 2017; Weiss, Allen, McGuigan and Whatman, 2017; Murray et al., 2017b). However, there have been a number of other potential calculation methods, time frames and mathematical complexities suggested since the method's inception (discussed in sections 2.7.9.2, 2.7.9.3 and 2.7.9.4 respectively). Since its first use, a number of studies have reported similar sweet spots, whereby the risk of injury is greater at the lower and higher end of acute:chronic ratios, with the following values representing the lowest risk in each respective study: 1.00-1.25 (Malone et al., 2017b), 1.0-1.49 (Weiss et al., 2017) and 0.6-1.5 (Stares et al., 2018). Whether or not a sweet spot exists in acute:chronic values is inconclusive, however, what is clear is that values exceeding an acute:chronic score of 1.5 appear to cause a higher injury risk with a number of different exact values reported; >1.6 (Hulin et al., 2016a), >1.76 for total distance >1.77 for accelerations (Bowen et al., 2017), >2.0 (Hulin et al., 2014; Malone et al., 2016; Murray et al., 2017b) and >2.11 (Hulin et al., 2016b).

In isolation, the acute:chronic workload ratio provides practitioners with a useful tool for daily management of athletes; however, the role of this measure must be considered in the context of other moderators and measures of load. For example, the analysis of the acute:chronic ratio has been shown to be affected by the chronic load status of the athlete with low chronic loads combined with spikes in acute:chronic associated with an increased risk, while high chronic loads have been shown as protective against workload spikes of > 1.5 (Hulin et al., 2016b; Stares et al., 2018). Similarly, using the acute:chronic ratio with respect to other injury risk factors such as player experience and aerobic fitness have shown the importance of analysing training load data in a multifactorial manner. For example, Malone et al. (2016) have demonstrated that players with less than 1 year of experience were at greater risk of injury compared with those with 2-3 and 4-6 years of experience, while players with poorer aerobic fitness were also at a greater risk when exposed to acute:chronic workload spikes of 1.5. In the context of rugby union, only one previous study has examined the relationship between the acute:chronic workload ratio (still training stress balance at the time of writing) and found unclear associations the acute:chronic workload ratio and injury risk, with more data required to clearly define the measure's utility (Cross et al., 2016b).

The acute:chronic workload ratio is a training load measure that can be used across multiple data types by practitioners to manage the athlete's training plan. Despite the association between the measure and injury risk, it has recently been shown that the tool does not predict injuries (Fanchini et al., 2018; Hulin and Gabbett, 2019), despite this claim in some research of this type (Hulin et al., 2016b; Hulin et al., 2016a). It is for this reason that the acute:chronic workload ratio should be used for the purpose of making informed decisions about an athlete's injury risk, having considered other moderating factors such as previous injury history, playing experience, match loads and player's physical fitness, as well as other measures of load, including acute and chronic loads exclusively (Hulin and Gabbett, 2019). With this in mind and the lack of clear associations between the measure and injury risk, further evidence to support or reject the utility of the acute:chronic workload ratio is required in the context of rugby union.

2.6.9.5 Week-to-week changes

Week-to-week change in load is a measure of training load similar to that of the acute: chronic workload ratio whereby the concept is designed to minimise the likelihood of an athlete being exposed to a large increase in training load over a short period of time. In the currently available literature, week-to-week change has been reported as both a percentage change and an absolute change in load. In AFL, absolute changes in sRPE load of 1250 arbitrary units (AU) have been shown to be high risk situations (OR:2.58, CIs:1.43-4.66)(Rogalski et al., 2013) while in soccer, injury risk was greater in players with large changes in week-to-week GPS loads, specifically using high speed running and sprinting metrics (Malone et al., 2018). To minimise the risk of injury, previously a guideline of no greater than 10% change has been suggested (Gabbett, 2016a), however, more recently, this "10% rule" has been questioned, with the author outlining the importance of context as to other markers of load (e.g. chronic load) when applying progressive changes to weekly loading patterns (Gabbett, 2018). In the case of rugby union, a 2SD change in the absolute load of an athlete (1069 AU) has shown a 60% increase in the risk of injury to a player (OR:1.58, CIs 0.98-2.54) (Cross et al., 2016b). Naturally, at certain times of the season, large changes in weekly load will be unavoidable for athletes; however, recognising the potential impact of these changes and their relation to injury is essential prior to prescription of such changes. Two such scenarios may occur at the start of a pre-season period after a period of rest and recovery or after a player has returned from injury. In the case of a returning player, where it is possible that a large week-to-week change will occur, understanding what effect this may have on their physical readiness is important when deciding if a player should return to full competitive action. Another measure which can be derived in a similar fashion to that of week-to-week change is that of differential load (Lazarus et al., 2017). This differential load represents a smoothed rate of change in load from one week to the next (Lazarus et al., 2017) and, therefore, presents a more smoothed value for analysis when analysing daily load values compared with rolling week-to-week change scores, minimising large variation day to day.

2.6.9.6 Summary

As demonstrated, there are a wide selection of available training load tools for practitioners working in athlete monitoring, each of which can be aggregated using the load metrics outlined in sections 2.6.9.2 – 2.6.9.5. Despite this, those working in the field must understand not only the impact of other moderating risk factors (Windt, Zumbo, Sporer, MacDonald and Gabbett, 2017) but also the potential multicollinearity of the training load variables used (Williams, Trewartha, Cross, Kemp and Stokes, 2017a). To overcome the potential issues arising from multicollinearity and to streamline the number of measures used by practitioners, methods such as principle component analysis have been suggested to objectively identify the most essential training load variables, while still capturing the distinct aspects of load associated with each measure (Williams et al., 2017a). This particular study demonstrated that in relation to training load and injury in rugby, a measure of cumulative load, change in load and acute load were most appropriate, accounting for 57, 24 and 9% of variation respectively. This illustrates the importance of capturing a range of derivative measures from training load data to assess injury risk.

2.6.10 Issues associated with load monitoring

2.6.10.1 Sample size & time scale

In this field of research, the generalisability of study findings are often limited by the sample size and the time scale over which the variables are measured. Often studies of this type are undertaken by practitioners or researchers with close links to one particular team, meaning that the data collated is from one source. This of course is a convenient sample in most cases; however, the generalisability of the outcomes to other teams in the same or different settings is limited given the potential medical or training structures in place at the club in the study. Of the 34 studies found to report the relationship between training load and injury risk using longitudinally collected data, the average number of players for whom data was captured, was 96 (median=46), with a range of 12-502. While the number of players itself does not cause a methodological issue, having fewer players exposed reduces the number of injuries which occur over the study period, limiting the statistical power of the study. Of the studies using data collected from multiple teams, two studies were conducted in rugby union, with Cross et al., (2016b) using 4 teams (n=173) and Brooks et al. (2008) using 12 teams (n=502). Although the larger of these studies by Brooks and colleagues provides valuable research into training volume and injury risk, the metrics used in this study were cruder than those used in Cross et al. (2016b) and more recent literature, therefore, limiting its applicability to modern day athlete management practices. Although not always feasible, the desire for larger sample sizes in studies of this type have been exemplified by some work demonstrating the decrease in total error and variance associated with larger studies, as displayed by simulated data from Carey et al. (2018).

One method of maximising the number of observations available to researchers and of minimising the risk of error is to increase the duration of the data collection. This will lead to an increase in the number of observations per player and, therefore, will increase the dataset, without the need for more than one team's worth of data. The majority of studies use one (Colby et al., 2014; Cross et al., 2016b; Malone et al., 2016; Malone et al., 2017c; Malone et al., 2018) or two (Hulin et al., 2016a; Hulin et al., 2016b; Murray, Gabbett, Townshend and Blanch, 2017a; Esmaeili et al., 2018) seasons worth of data, while there are fewer using more than 2 (3 seasons (Carey et al., 2017c), 4 seasons (Colby et al., 2017) and 6 seasons (Hulin et al., 2014)). In the aforementioned study (Windt et al., 2018), of the 34 studies identified using longitudinal surveillance training and injury data, the range of data collection periods spanned from 14 weeks through to 6 years. Given the desire for large sample sizes and prolonged tracking periods, the design of this thesis is such that both the number of teams as well as the period of collection was maximised to minimise the risk of Type II errors.

2.6.10.2 Calculation method

In the first use of the acute:chronic workload ratio (training stress balance), a one-week acute load and a four- week rolling average load were used to assess the relationship between this measure and athlete injury risk (Hulin et al., 2014). Following this, a similar one-week to four-week rolling average load was used (Blanch and Gabbett, 2016). Soon after the publication of Gabbett's "Training-injury prevention paradox" paper (2016a), which advocated the use of such rolling averages, Menaspa (2017) questioned the use of rolling averages when calculating the acute:chronic workload ratio. In this correspondence piece, Menaspa outlined how rolling averages did not represent physiological training adaptation, demonstrating three examples whereby athletes undertaking largely different loading patterns were represented by the same acute:chronic score due to the value placed on old training values and new training values being the same using a rolling average system. Drew et al. (2017a) suggested that although a better alternative may well be available, until such time that this alternative has been demonstrated as clearly more effective, the use of a rolling average approach is evidence-based and has been shown by previous work as being associated with injury risk. In support of Menaspa, Williams et al. (2016b) outlined how the decaying nature of both fitness and fatigue were not accounted for when using a rolling average. To overcome this, the authors suggested as an alternative the use of an exponentially-weighted moving average (EWMA), which would assign a smaller weight to each load value, as they went progressively further back in time (Hunter, 1986; Williams et al., 2016b) Using this calculation as opposed to the rolling average calculation would ensure that the positive fitness effects of training would decay over a greater period than that of the acute fatigue effects. This proposed exponentially weighted average would also be tailored to the timeframes of relevance to the sport, with the user being able to adjust the decay rate by altering the value “N” in equation 1.

Equation 1:

$$EWMA_{today} = Load_{today} \times \lambda_{\alpha} + ((1 - \lambda_{\alpha}) \times EWMA_{yesterday}$$

$$where\ \lambda_{\alpha} = \frac{2}{N+1}$$

In this equation, λ_{α} has a value of between 0 and 1 representing the degree of decay that is applied to the day’s acute:chronic value, with a higher value discounting older observations at a higher rate. Since the proposal to use exponentially-weighted averages instead of rolling averages, a number of studies have examined the differences in effectiveness of the two measures when modelling training load and injury risk. The first of these studies demonstrated increased sensitivity of the EWMA measure, reporting a far greater amount of variance explained by the EWMA method compared to a rolling average (Murray et al., 2017a). Despite the ability of an acute:chronic workload ratio (calculated using either a rolling or EWMA) to detect an increasing injury risk when a large acute:chronic workload spike occurred, the ability of the EWMA to detect change at lower values was greater than that of a rolling average. A second paper has also demonstrated the potential utility of the EWMA method with a greater effect reported when training load measures were calculated using this method (Esmaeili et al., 2018). Despite the apparent improved sensitivity and greater effects associated with the EWMA, both methods have been used in the latest literature. Thus support for both methods of acute:chronic calculation exists and, therefore, it seems prudent that both analysis methods should be undertaken in this thesis to establish which method is the most appropriate.

2.6.10.3 Acute/chronic time windows

Further to the method of calculation used, the periods over which acute and chronic workloads are measured should be considered within the context of each individual sport. Traditionally, acute and chronic time periods are one week and four weeks in duration. Despite this, other time periods have been suggested for both acute and chronic loads in the calculation of the acute:chronic workload ratio. In AFL, Carey and colleagues (2017a) tested 48 combinations of acute:chronic workload ratios using interactions of eight acute loads (2 to 9 days) and six chronic loads (12,18,21,28,32,35 days). On average, the combination associated with the highest R^2 value was a 6:14 day acute chronic ratio (R^2=0.91). Despite this, looking at individual training load variables (e.g. different GPS metrics) was shown to indicate that the best value model may be specific to the measure being used. In the context of the most commonly used 7 to 28 day acute:chronic ratio, when measuring the total distance GPS metric, this combination was shown to display low R^2 values ranging from 0.04-0.41. The recommendations of this study outline the need for a similar analysis to be undertaken for each team, while testing different training load metrics. Importantly, variations in the training schedules of different sports may account for which combination produces the most information about injury risk; for example, in AFL, a 3 day acute period may include the main training session prior to a game, but never the previous match, while a 6 day acute period may include the load associated with the previous match (Carey et al., 2017a). It is for this reason that in the context of rugby union, a similar analysis would be appropriate to account for the training practices of clubs in preparation for upcoming fixtures. In a more recent study of AFL (Stares et al., 2018), using the area under the curve (AUC) as the measure of model predictive ability, the traditional 7 to 28 day acute:chronic workload ratio was deemed as useful as any of the other combinations, which included 7, 14, 21, 28, 35, 42, 48 and 56 day chronic loads. However, it must be recognised that this study looked not only at the acute:chronic metric, but also accounted for the chronic load of each athlete. Given the findings of these studies, it is clear that an analysis of differing time periods should be undertaken to establish the most appropriate in the context of rugby union.

2.6.10.4 Mathematical coupling

Within the calculation of the acute:chronic workload ratio, by virtue of its inclusion in the chronic load period, the acute load constitutes a substantial portion of the chronic load itself (Lolli et al., 2017). As a result of this, it is noted that there is a potential for mathematical coupling, whereby both research inferences and monitoring practices are compromised by the existence of spurious correlations. That is, a correlation between two variables irrespective of any true biological or physiological association (Lolli et al., 2017). Lolli et al. (2017) express concern over the inclusion of the acute period within the chronic workload period and suggest that uncoupling of the data should occur to ensure the validity of the measure and to reduce the bias associated with the current calculation of the acute: chronic workload ratio. In response, Windt and Gabbett (2018) provided an overview of how mathematical coupling may affect the acute:chronic workload ratio. During constant loading conditions, the acute load represents 25% of the chronic load and as the acute load spikes, this acute load accounts for a greater proportion of the chronic load. The acute:chronic workload ratio essentially represents how many times greater the proportion is than 25%, with the value of this number able to approach but never exceed a value of 4, when the acute load is responsible for all of the chronic load. Given this, Windt and Gabbett (2018) highlight the expected nature of the correlation values of 0.5 reported by Lolli and colleagues as these represent an r^2 value of 0.25% of the variance that is the acute load. While it is clear that mathematical coupling alongside other methodological factors remain important to consider, Windt and Gabbett (2018) stress the importance of understanding the implications of the methods used as well as clearly outlining how the acute:chronic workload ratio is calculated in any research.

2.6.10.5 Latent period

The latent period associated with analyses of training load and injury data refers to the period over which a spike in load can have an influence over injury risk. In the current literature regarding the latent period, some research suggests that a spike in workload can negatively impact upon performance for up to 4 weeks (Orchard et al., 2009; Drew and Finch, 2016; Stares et al., 2018). In contrast to this, the use of two and five day injury lags demonstrated no effect on model performance and, therefore, the use of a forward looking latent period does not significantly explain variations in injury risk patterns (Carey et al., 2017a). While it is recommended by Windt et al. (2018) that a latent period be included to account for the role of temporality in the relationship between training load and injury risk, the evidence supporting the use of a latent period demonstrates conflicting evidence, while the best practice for including such a period is not well described within the literature.

2.6.10.6 Other considerations

Despite significant support and uptake for the acute:chronic workload ratio in recent years, several authors have critiqued the metric, including Buchheit (2017) and Lolli et al. (2018). The use of ratios is usually undertaken to normalise one variable (chronic load) that is perceived to have an important influence over another (acute load) (Lolli et al., 2018). These authors suggest that there is little empirical evidence for the need to normalise acute load against chronic load, when the acute load is a clearly useful predictor in absolute terms alone. The consequences of such a normalisation process, where there is no need is adding only noise to injury models; therefore, its inclusion should be appraised with larger datasets prior to making assumption of its importance in injury risk. In another critique, Buchheit (2017) clearly outlines how the potential benefit of the acute:chronic workload ratio is straightforward, however, there are some limitations associated with the measure's use from a practical standpoint. In some sports, where practitioners are in full control of the training plans of their athletes, the use of the acute:chronic measure is somewhat easier to apply. However, in sports like soccer and rugby, where control of athlete training may be limited during periods of the season, a number of methodological considerations must be accounted for. Buchheit (2017) outlines some of the scenarios in which difficulty can occur, including the off-season when training monitoring does not occur and the international windows, when the integration of data from different systems may be required if the international teams use different systems to clubs. Further to this, should data not be captured during this time, a number of weeks will be required to return to "normal" ratios for each player. As a solution, Buchheit (2014) suggested the use of the sRPE measure, which can be utilised in any setting by the individual player, irrespective of the monitoring practices of the international team; however, this solution is limited in that it is unlikely to be sensitive to subtle differences in certain high risk measures such as sprinting. These critiques, in the context of conducting research, demonstrate the need to have well-defined methods to account for such situations and to approach the use of monitoring measures with critical thought as to the amount of valuable information they provide compared to the potential volume of noise in the data.

2.6.10.7 Association vs prediction

Another desired use for training load and injury data is in the context of injury prediction. In the context of training load analysis, although the association between injury risk and training load is well documented, it is not possible to infer predictive values, as suggested in some articles (Hulin et al., 2016b; Hulin et al., 2016a). In fact, since the publication of these articles, the authors have reviewed their manuscripts and described the leap from association to prediction as "regrettable", outlining how the intention of the papers was to assist practitioners in making informed decisions regarding the risk to their athletes (Hulin and Gabbett, 2019). Although effective injury forecasting has been demonstrated in some sports using advanced machine learning techniques (Rossi et al., 2018), the isolated use of the acute:chronic workload ratio as a predictive tool has been shown as a poor marker of prediction with area under the curve values of 0.55 to 0.60 as well as low measure sensitivity (12.5-43.1%) reported, despite the association between the sRPE derived load and injury risk (Fanchini et al., 2018). Although the future of injury prediction using training load data may be aided by improvements in statistical understanding and modelling, the current use of such variables is valuable only when examined in the context of other risk factors, such as previous injury. It is, therefore, likely that research in this area should focus on helping to inform coaches and practitioners about the relationship between training load and injury in the context of other moderating factors until such methods for injury forecasting improve.

2.6.11 Statistical considerations in training load analyses

2.6.11.1 Discretisation

Data discretisation involves the transformation of continuous data into discrete categories, such as median splits, percentiles, z-score categories and arbitrary bins, as utilised in previous training load research (Carey et al., 2018). Data discretisation has a number of potential limitations, including: lower statistical power; lack of ability to assess within-category variation; inflated false discovery rate; and the potential for bias when selecting reference categories (Carey et al., 2018). To demonstrate the risks associated with this process in training load analysis, Carey et al. (2018) produced a number of simulated datasets with known injury risk profiles (U-Shaped, Flat and S-Shaped) and sample sizes of 1000 and 5000 observations to represent one season and multi-season studies, respectively. With the simulated data, three types of commonly used discretisation processes were undertaken: using z-scores for the acute:chronic workload ratio; split into 5 categories with arbitrary cut points; and split into quartiles. When comparing these discrete analysis methods with complex continuous methods, including cubic splines and fractional polynomials, the continuous method demonstrated lower root mean square error, an decrease in false discovery rates and an decrease in false rejection rates. Although this comparison demonstrated improvements in model accuracy using continuous methods of analysis, it also demonstrated that increasing sample size from 1000 to 5000 observations decreased the error and variance associated with both methods. It is, therefore, advised that larger sample sizes should be used in studies of this type to minimise error and to use continuous analysis methods where possible.

2.6.11.2. Other statistical considerations when modelling training load data

As previously mentioned, injury aetiology is a multifactorial and dynamic process (Meeuwisse et al., 2007) and, therefore, when examining the association between training load and injury risk, attributing injury to any single risk factor has been described as an oversimplification of a highly complex process (Windt et al., 2017). To truly capture the association between any two variables, it is essential that other injury risk factors be included in models to understand the role they play in mediating or moderating the workload injury relationship (Windt et al., 2017). Where mediators could be considered as intermediary steps to the onset of an injury, moderators can be considered like 'dimmer switches' in modifying the effect of variables on the outcome of interest (Windt et al., 2017). The inclusion of variables such as previous injury (Williams et al., 2017c), previous concussion (Cross et al., 2015), match loads (Williams et al., 2017c) and other load measures (e.g. chronic load (Esmaeili et al., 2018)) have been shown to be important risk factors in injury risk and, therefore, will be included in assessing the mediating and moderating role they play when combined with training load in the current thesis.

In a recent review of the challenges associated with statistical modelling of longitudinal data of this type, Windt et al. (2018) reported this lack of incorporation of previously identified risk factors as one of the failings of current literature in the area. This review suggested that the analysis of training load data in isolation fails to control for confounding variables and, therefore, the findings themselves may be spurious. To ensure the robustness of any modelling of this complex relationship, it is suggested that a number of considerations be made when deciding on a statistical strategy including: dealing with repeated measures, accounting for missing or unbalanced data, separation of between and within person effects, time varying and time invariant factors, and specifying the role of temporality. Given these considerations, it is imperative that statistical model selection is appropriate to the type of data because to use an incorrect model or to incorrectly use an otherwise correct model would result in bias and potentially create false conclusions (Windt et al., 2018). In this thesis, therefore, model selection will be undertaken accounting for these considerations with the methods outlined in each respective chapter.

2.6.12 Acute:chronic workload ratio: Recent critique

Several of the methodological considerations for calculating the acute:chronic workload ratio have been outlined in the previous sections; however, more recently a number of critiques specific to the origins and utility of the technique have emerged. In an open letter, Impellizzeri and colleagues (2019b) highlight flaws in the methodology of the production of the commonly cited acute:chronic 'sweet spot' of 0.8 to 1.3 (Gabbett, 2016a). These flaws include the aggregation of data taken from uniquely different sports and load constructs. Further to this, in the production of the 'sweet spot' graph reported in Gabbett (2016a), Impellizzeri et al, (2019b) outline the adjustments made to originally discretised data to produce apparently continuous variables. As this data had previously been discretised, to treat it as continuous data is not correct and further adds to the issues surrounding discretisation previously discussed in section 2.6.11 (Carey et al., 2018).

In a further paper exploring the current limitations of the acute:chronic workload ratio, Wang and colleague (2019) also demonstrate some of the issues surrounding the use of coupled loads, the exponentially weighted moving averages and discretised data. Not only do they propose useful methodological refinements to the acute:chronic workload ratio, but also propose some further challenegs including, the lack of ability to account for tapering, the production of common principles around sparse data and unmeasured confounding. These important methodological considerations will be largely be addressed throughout this PhD thesis, where possible, by using large sample sizes to minimise the sparsity of data as well as adjusting for multiple well known confounding variables. Despite the mounting limitations and challenges surrounding the use of the acute:chronic workload ratio, the use of the method within this thesis is important to establish principles for rugby union, given the widespread uptake of the method in athlete monitoring.

2.6.13 Summary

This review of literature has demonstrated not only the theoretical underpinning associated with studies of injury risk but also highlighted some of the key previously identified risk factors that are common across sport and in rugby union in particular. While there is significant evidence of the effect of injury risk factors in popular sports such as soccer, Australian rules football and rugby league, there are a limited number of studies within elite rugby union. In particular, there is only one study that has considered the influence of training load on injury risk using both a measure of duration and intensity (Cross et al., 2016b), while one further study exists using the more crude measure of training volume (Brooks et al., 2008). Further, given the rapidly advancing knowledge surrounding the methods used in analysis of training load data (including differences in acute and chronic time windows (Carey et al., 2017a; Stares et al., 2018), the effects of mathematical averaging techniques (Menaspa, 2017; Williams et al., 2016b; Murray et al., 2017a; Esmaeili et al., 2018) and the effects of mathematical coupling (Lolli et al., 2017)), it appears prudent that an investigation of the most appropriate methods in a rugby union setting be undertaken. Of the previously conducted studies in training load and injury risk, the median number of players included was 46 (Windt et al., 2018). These studies have often been limited to one team studies, while studies with larger sample sizes have been recommended to reduce the likelihood of error (Carey et al., 2018). Finally, within the current literature it appears that a significant number of studies have disregarded the importance of previously identified risk factors, such as previous injury history, and, therefore, offers a potential opportunity to expand upon current knowledge by documenting the importance of training load, in the context of these other potential covariates.

2.6.14 Rationale for the current work

It is clear that injury is responsible for a significant burden upon teams in professional sport, whether that be from a financial (Hickey, 2014), long term health (Davies et al., 2017) or performance (Williams et al., 2015) perspective. Given the negative consequences of injury in sport, as well as the associated high rates in rugby union, it is vital that any intrinsic or extrinsic risk factors are identified, in particular those that are modifiable. One such variable is that of training load as prescribed by the coaching staff of the particular athlete. As outlined in the literature review, despite evidence for a relationship between training load and injury risk, there is a dearth of literature pertaining to rugby union specifically. Further to this, the lack of inclusion of known risk factors in other injury risk studies allows for scope to investigate load in the context of other known risk factors. This study will, therefore, aim to overcome some of the known current limitations and target a more holistic image of injury risk, which will hopefully allow for a better understanding of the importance of training load as a modifiable injury risk factor in elite rugby union.

CHAPTER 3

Patterns of training volume and injury risk in elite rugby union: an analysis of 1.4 million hours of training exposure over eleven seasons

3.1. Introduction:

Rugby union is a field-based team game composed of long bouts of low intensity movement or rest interspersed by short bouts of high intensity locomotor or contact activity (Roberts, Trewartha, Higgitt, El-Abd and Stokes, 2008). While all players are exposed to both contact and running demands, backs cover greater distances at higher speeds, while forwards are involved in more than twice the number of contact events and cover greater distances at lower speeds (Quarrie et al., 2013; Cunniffe et al., 2009; Dubois et al., 2017). To meet the physical demands and the high skill levels required to play elite rugby union, a number of training modalities are employed to prepare players, including aerobic conditioning, high intensity interval training, strength training and sport specific skills sessions(Tee, Lambert and Coopoo, 2016; Argus, Gill, Keogh, Hopkins and Beaven, 2009; Gannon, Stokes and Trewartha, 2016; McLaren et al., 2017). The purpose of training is "to prepare players for the physical demands of competition, including the most demanding passages of play" (Page 1, Gabbett, 2016a) Previous studies provide a useful overview of rugby training strategies (Argus et al., 2009; Tee et al., 2016; Gannon et al., 2016; McLaren et al., 2017), however, it is difficult to generalise the findings, as they related to single club studies and, therefore, the results may only reflect the conditioning strategies specific to those clubs. Another limitation to previous studies is the relatively short duration over which they were conducted (usually weeks, months or 1-2 seasons); hence, they do not offer an understanding of how rugby training may have changed over time. In the 11 seasons of data collection included in this study, the use of technology to guide training as well as the management of athletes has received significant attention in both research and practice. While this is the case, there is little information surrounding how these changes have positively or negatively influenced training injury rates or whether training volumes have changed in accordance with these new data driven programs. Further to this, Quarrie et al. (2016) highlighted the importance of managing training load and outlined the need for large scale research projects to provide sufficient evidence to inform decision-making processes regarding player load and welfare..

The incidence of match injury in rugby union is relatively high compared with other team sports [81 injuries per 1000 player-hours of exposure (Williams et al., 2013)]: a much lower incidence of training injuries [3.0 per 1000 player-hours of training (Williams et al., 2013)], means that the impact of training injuries is often overlooked. Importantly, high training exposure compared to match exposure means the absolute number of injuries associated with training is still relatively high: Brooks et al. (2005b) reported that over a two-season period, 395 injuries were the result of training activities. While match injuries are often the result of unpredictable game events and hence difficult to prevent, training is conducted in a largely controllable environment and, therefore, it may be considered easier to reduce injuries in this environment (Williams et al., 2015). Therefore, in an effort to reduce the overall time loss associated with injury in rugby union, the focus of these efforts may be best placed in training, compared with match-play.

Although several studies have examined patterns of training activity in rugby union (Brooks et al., 2005b; Argus et al., 2009; Gannon et al., 2016), there is a sparsity of information regarding changes to the composition and volume of training over time and the impact of these changes on the incidence, severity and type of training injuries. Consequently, the aim of this study was to assess longitudinal changes in volume and type of training, and to explore the effect of these changes on training injury over eleven seasons.

3.2 Methods:

3.2.1 Participants

Over the 11-season period (2007/08 to 2017/18), a mean of 600 (standard deviation (SD): 72, range: 505-725) players per season consented to participate in the study, with a total of 5998 player-seasons captured over the entire period (some players were involved in multiple seasons). Training exposure and injury data were collected as part of the Rugby Football Union injury surveillance project, which included England's 12 Premiership clubs each season. All consenting players deemed eligible for first team selection were included in the study. The study was subject to ethical approval by the host academic institutions [University of Nottingham (2007- 2012) and University of Bath (2011-2018)].

3.2.2 Procedures

In each club, match and training injury data were collected by medical staff and training data by conditioning or sports science staff. Training data were captured using paper-based forms from 2007/08 through 2011/12 and manually entered into a database at the host university. From the 2012/13 season, training data were captured using a bespoke online platform, "Elitehub". Injury data were captured according to the rugby consensus statement (Fuller et al., 2007c) using paper-based forms from 2007/08 through 2012/13 and manually entered into a database. From the 2013/14 season, injury data were captured using an online platform, "Rugby Squad" (The Sports Office UK Ltd). For each injury, data pertaining to the count, severity, burden, mechanism and site of injury were documented, while the type of training during which the injury occurred was also recorded.. Training volume data were collected under five categories: full-contact (rugby skills training in which contact occurred without the use of external padding), semi-contact (rugby skills training with the use of pads or bags), non-contact (rugby skills training without contact between players), conditioning (non-gym-based; i.e., conditioning training other than gym-based activities, e.g., running endurance, speed/agility, power etc.) and conditioning (gym-based), with warm up and cool-down not included in total training time (which was calculated as the accumulated time spent in each category). Training volume was reported as the number of players partaking in each session type during the week and the number of minutes spent performing each training type; this was then multiplied to calculate training volume in each category and summed to get total training volume. Only training injuries were included in this analysis and were defined as “any injury that resulted in a player being unable to take a full part in future rugby training or match play for more than 24 hours from midnight at the end of the day the injury was sustained” (Fuller et al., 2007c). Injury burden was reported as the number of days absence per 1000 player-hours of exposure and was defined as the product of incidence and severity (Brooks et al., 2005a; Brooks et al., 2005b).

3.2.3 Data Analysis

Injury incidence was calculated as count of injury per 1000 player-hours (Brooks et al., 2005a; Brooks et al., 2005b). Mean severity was calculated as the total number of days absence divided by the number of injuries while median severity was calculated as the midpoint in the range of severities associated with the injuries. Median severities were calculated to demonstrate the effect that a small number of high severity injuries can impose on mean severity values. Injury burden (days absence/1000 player-hours) was calculated as the product of injury incidence and mean severity (Brooks et al., 2005a). Corresponding 95% confidence intervals (CI) were calculated for incidence, severity and burden values. A one-way repeated measures ANOVA, using a Greenhouse-Geisser correction to account for sphericity (Greenhouse and Geisser, 1959), was used to calculate whether the amount of training in each category had changed significantly over the duration of the study period. Effect sizes were calculated as a partial eta squared (η_p^2) and assessed using the guidelines proposed by Cohen (1988) (0.01=small, 0.06= moderate, 0.14=large effect) Linear regression was used to identify significant trends in injury incidence, severity and burden over time. Further to this, linear regression was used to establish the rate of change in injury severity over time for each of the training categories. Statistical significance was set at $P<0.05$; no adjustments were made for the number of statistical tests undertaken. All statistical analyses were completed in SPSS (IBM SPSS Statistics, Version 24, 2018).

3.3 Results:

3.3.1 Training volume

During the period 2007/08 to 2017/18, a total of 1,501,606 player-hours of training volume (full-contact: 97,855 player-hours; semi-contact: 237,322 player-hours; non-contact: 459,086 player-hours; conditioning, non-gym-based: 220,222 player-hours; conditioning, gym-based: 487,121 player-hours) and 3,782 training injuries were recorded (full-contact: 889; semi-contact: 851; non-contact: 653; conditioning, non-gym-based: 913; conditioning, gym-based: 331; unknown: 145). The mean time spent training over the entire study period was 6 hrs 48 minutes/player/week (95% CI: 6 hrs 30 mins to 7 hrs 6 mins), with monthly differences evident within seasons (Figures 3.1A and 3.1B). July, when pre-season training began, showed the highest mean number of training hours at 10 hrs 18 mins. June (3 hrs 24 mins) and May (2 hrs 30 mins), the off-season period, showed the lowest. Over the study period, conditioning (gym-based) and non-contact rugby skills training accounted for the most time on average, with weekly means of 2 hrs 12 mins and 2 hrs 6 mins, respectively. Semi-contact and conditioning (non-gym-based) accounted for a mean of 1 hr per week, while the least amount of time was spent in full-contact rugby skills training (24 mins/player/week). During the season, the focus of training and time spent in different training categories changed. For example, in July, gym-based conditioning and non-gym-based conditioning accounted for 3 hrs 48 mins and 3 hrs 18 mins, respectively, whereas in April these accounted for just 1 hr 48 mins and 30 mins. Despite some within (range: 6–84 mins per week) and between (range: 36-54 mins per week) club variation, no statistically significant changes in training time were seen within clubs over the 11-season period (full-contact: F=1.437, P =0.315, η_p^2=0.324, large effect; semi-contact; F=0.407, P =0.769, η_p^2= 0.075, moderate effect; non-contact; F=1.154, P =0.350, η_p^2= 0.141, large effect; conditioning (non-gym-based): F=1.831, P =0.186, η_p^2= 0.234, large effect; conditioning (gym-based): F=2.101, P =0.141, η_p^2=0.231, large effect).

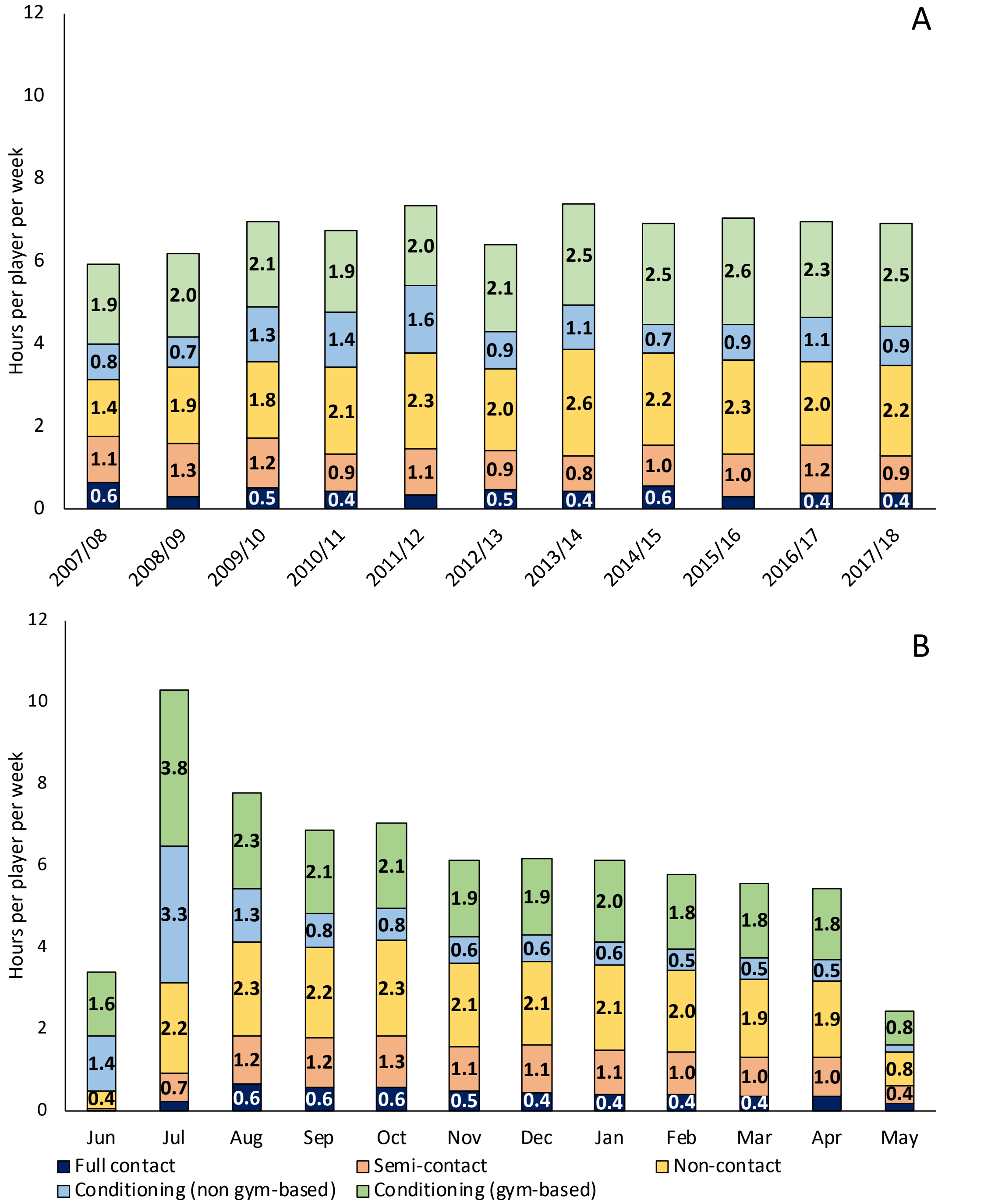

Figure 3.1: Average number of hours training per week per player by (A) season and (B) month. Values shown represent mean number of hours per player per week. Values less than 0.4 (24 mins per week) are not labelled for clarity.

3.3.2 Training injury incidence

The mean number of training injuries occurring per season was 344 (29 per club), with the highest number of injuries reported in the 2017/18 season at 438 (mean: 37 per club):Figure 3.2(A), Table 3.1. Over the study period, there was no significant change in the incidence of injury overall (Change per season: -0.01/ 1000 player-hours (95% CIs: -0.09-0.05), P =0.69). Individual seasons did however show fluctuation in risk with the 2015/16 season falling below 2 injuries/1000 player-hours. Full contact rugby skills training accounted for the highest injury incidence in all but the 2014/15 season, with a mean of 9.6 per 1000 hours (Figure 3.2(B)). Conditioning (gym-based) was consistently the activity with the lowest incidence and little between-season variation (mean: 0.7/1000 player-hours, SD: 0.2/1000 player-hours). Across all rugby skill-based components, the incidence of injury was 4.9 per 1000 hours (SD: 1.5), while the combined conditioning components demonstrated a rate of 2.5 per 1000 hours (SD: 0.4).

Table 3.1: Summary of training injury data (2007-2018) including injury count, injuries as proportion of all recorded injuries, exposure, incidence, median severity, mean severity, burden.

Season	Injury count	Proportion of all injuries (%)	Exposure, (hours)	Incidence (number per 1000 player-hrs)	Median severity (days absence)	Mean severity (days absence)	Burden (days absence per 1000 player-hrs)
2007-08	318	33 (29-36)	106000	3.0 (2.7-3.3)	9 (8-10)	17 (15-19)	51 (46-57)
2008-09	258	25 (22-28)	103200	2.5 (2.2-2.8)	11 (9-12)	22 (19-25)	55 (49-62)
2009-10	298	32 (28-36)	119200	2.5 (2.2-2.8)	9 (8-10)	20 (18-22)	50 (45-56)
2010-11	340	31 (28-35)	117241	2.9 (2.6-3.2)	11 (10-12)	21 (19-23)	61 (55-68)
2011-12	323	33 (30-37)	129200	2.5(2.2-2.8)	10 (9-11)	22 (20-25)	55 (49-61)
2012-13	335	36 (33-40)	128846	2.6 (2.3-2.9)	13 (12-14)	29 (26-32)	75 (68-84)
2013-14	414	36 (33- 40)	142759	2.9 (2.6-3.2)	12 (11-13)	25(23-28)	73 (66-80)
2014-15	325	34 (30-37)	141304	2.3 (2.1-2.6)	10 (9-11)	28 (25-31)	64 (58-72)
2015-16	304	40 (36-45)	159398	1.9 (1.7-2.1)	17 (15-19)	30 (27-34)	57 (51-64)
2016-17	429	36 (32-39)	147983	2.9 (2.6-3.2)	12 (11-13)	33 (30-36)	96 (87-105)
2017-18	438	38 (35-42)	152533	2.9 (2.6-3.2)	17 (15-18)	37 (34-41)	106 (97-117)

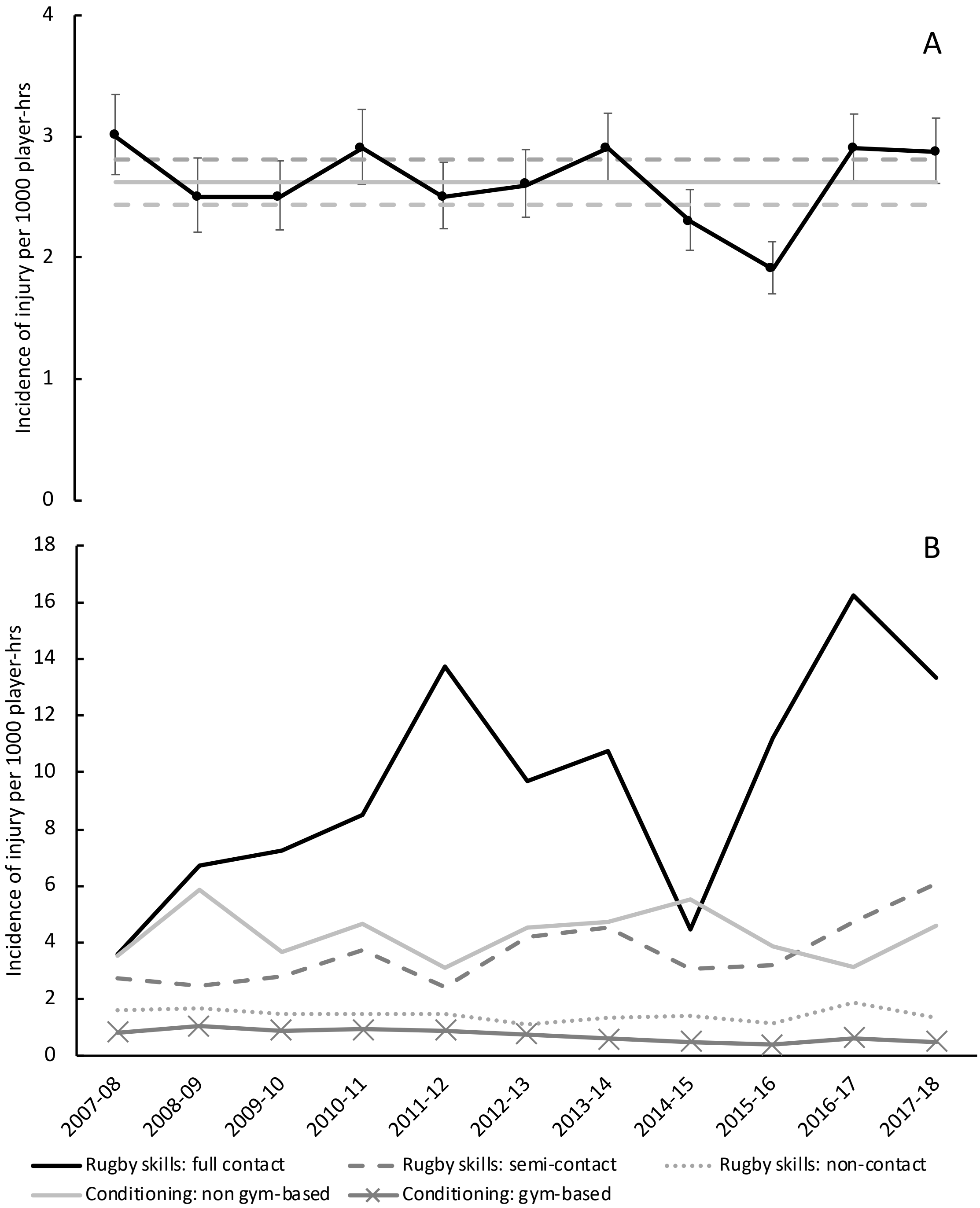

Figure 3.2: Training injury incidence for the seasons 2007-2018. (A) all training exposure types combined (B) training exposure by categories. Data points in Figure 3.2(A) represent the seasonal mean and the error bars 95% CI values; the solid grey line represents the period mean and the broken grey lines the 95% CIs for the mean.

3.3.3 Training injury severity

Mean severity of training injuries rose in all but two seasons, with the 2017/18 season showing the highest value at 37 days per injury (Figure 3.3(A)). Over the study period, the mean severity of injury rose by 1.7 days on average each season (B= 1.74; *P* <0.01: Table 3.2). Median severity of injury rose from 9 days in 2007/08 to 17 days in 2017/18, a rise of 0.8 days per season (Table 3.1). When injury severity is considered by training type (Figure 3.3(B)), no single type was consistently associated with the highest severity of injury. In all but two seasons, the training type with the lowest mean injury severity was conditioning (gym-based). Each of the training categories demonstrated an upward trend in injury severity but the rate of increase differed between the training types. Conditioning (non-gym-based) had the highest rate of increase in mean severity, rising an average of 2.4 days per season (B=2.43, *P* <0.01), while conditioning (gym-based) training displayed the lowest rate of change at 0.8 days per season (B= 0.76, *P* =0.13: Table 3.2).

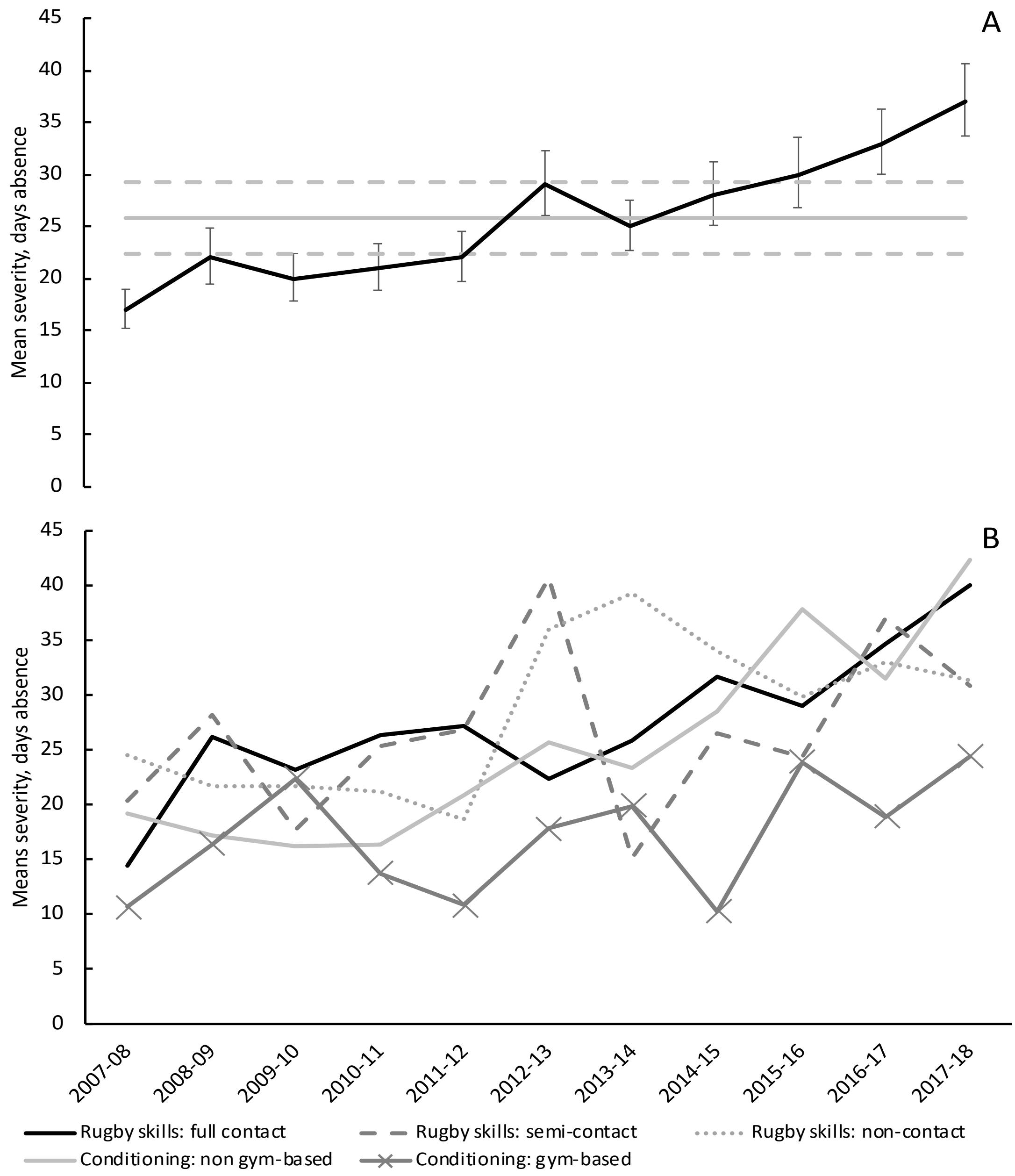

Figure 3.3: Training injury severity, 2007-08 to 2017-18. (A): all session types combined (B): by session type. Data points in Figure 3.3A) represent the seasonal mean and the error bars 95%

CI values; the solid grey line represents the period mean and the broken grey lines the 95% CIs for the mean.

Table 3.2: Regression analysis: season-on-season change in mean injury severity 2007-08 to 2017-18

Training Type	Change per season	P-value	5-year change
Rugby skills: full contact	1.77 (0.96-2.59)	<0.01	9 day rise in severity
Rugby skills: semi-contact	0.90 (-0.72-2.52)	0.24	5 day rise in severity
Rugby skills: non-contact	1.31 (0.11-2.51)	0.04	7 day rise in severity
Conditioning: non-gym based	2.43 (1.55-3.31)	<0.01	12 day rise in severity
Conditioning: gym-based	0.76 (-0.26-1.79)	0.13	4 day rise in severity
All training types	1.74 (1.27-2.20)	<0.01	9 day rise in severity

3.3.4 Training injury burden

The burden of training injuries rose significantly over the study period (Change per season: 4.4 days absence per 1000 hours (95% CIs: 1.26-6.42), *P* =0.004: Figure 3.4(A)). This rise was particularly noticeable during the 2016/17 and 2017/18 seasons when the burden was substantially higher than that of the total period as a whole. When analysed by training type, over the same 2-season period a similar rise was seen for full contact training, where burdens of 562 and 533 days absence per 1000 player-hours were recorded, respectively (Figure 3.4(B)).

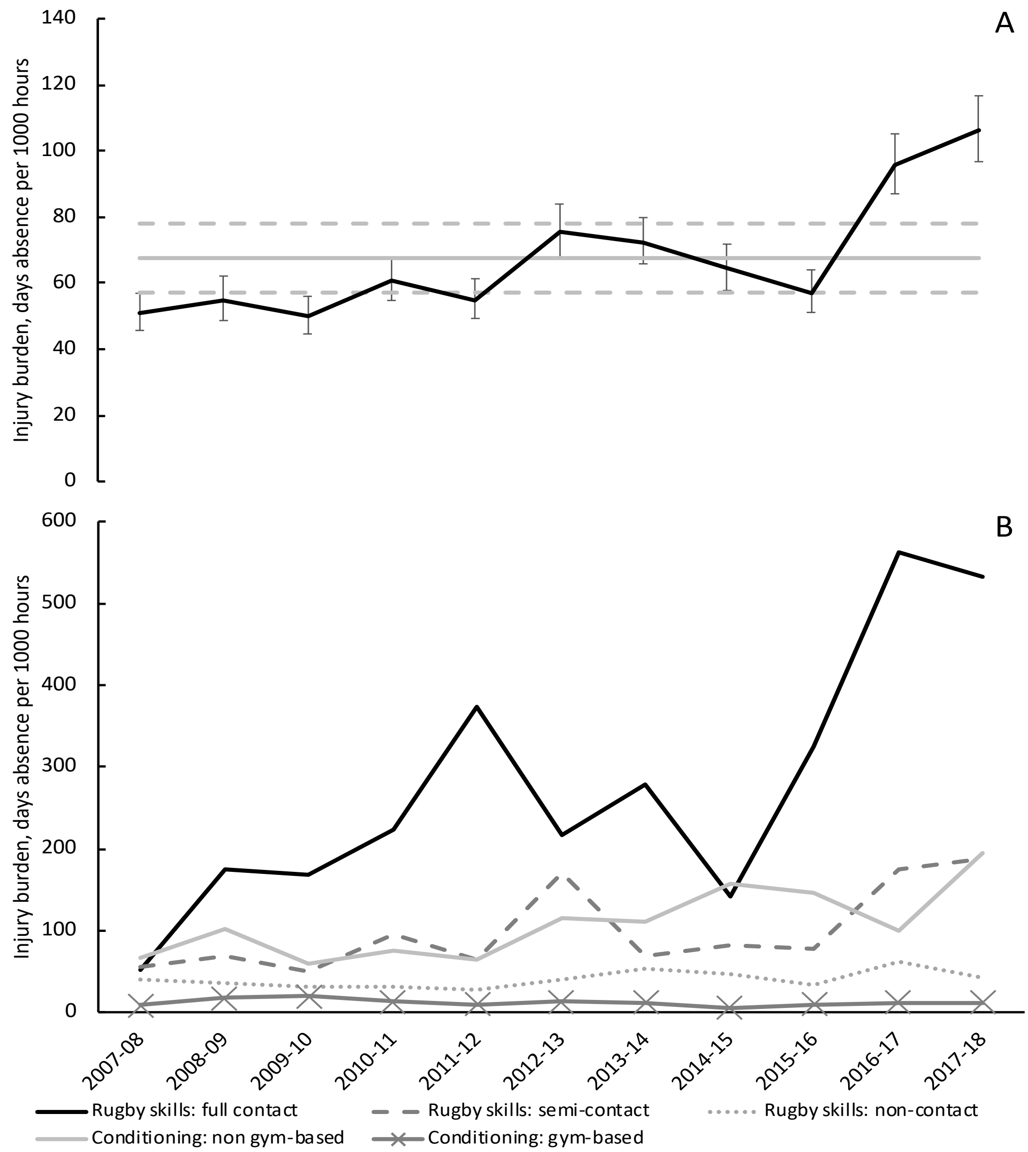

Figure 3.4: Training injury burden for the seasons 2007-2018. (A)= all session types combined (B)= broken down by session type. Grey lines in Figure 3.4(A) represent the period mean and 95% CI's around the mean.

3.3.5 Injury mechanism

There was a change in coding structure of injury mechanism in the 2009/10 season, and, therefore, the analysis of injury mechanism includes the seasons from 2009/10 to 2017/18 (Figure 3.5). Running was the most common training injury mechanism (1.1/1000 player-hours), followed by being tackled (0.19/1000 player-hours), accidental collisions (0.16/1000 player-hours) and tackling (0.14/1000 player-hours). The three most severe training injury events were kicking (40 days), scrummaging (39 days) and non-accidental collision (39 days); however, kicking and non-accidental collisions were the rarest events leading to just 35 and 30 injuries respectively (compared to 1300 running injuries) over the study period.

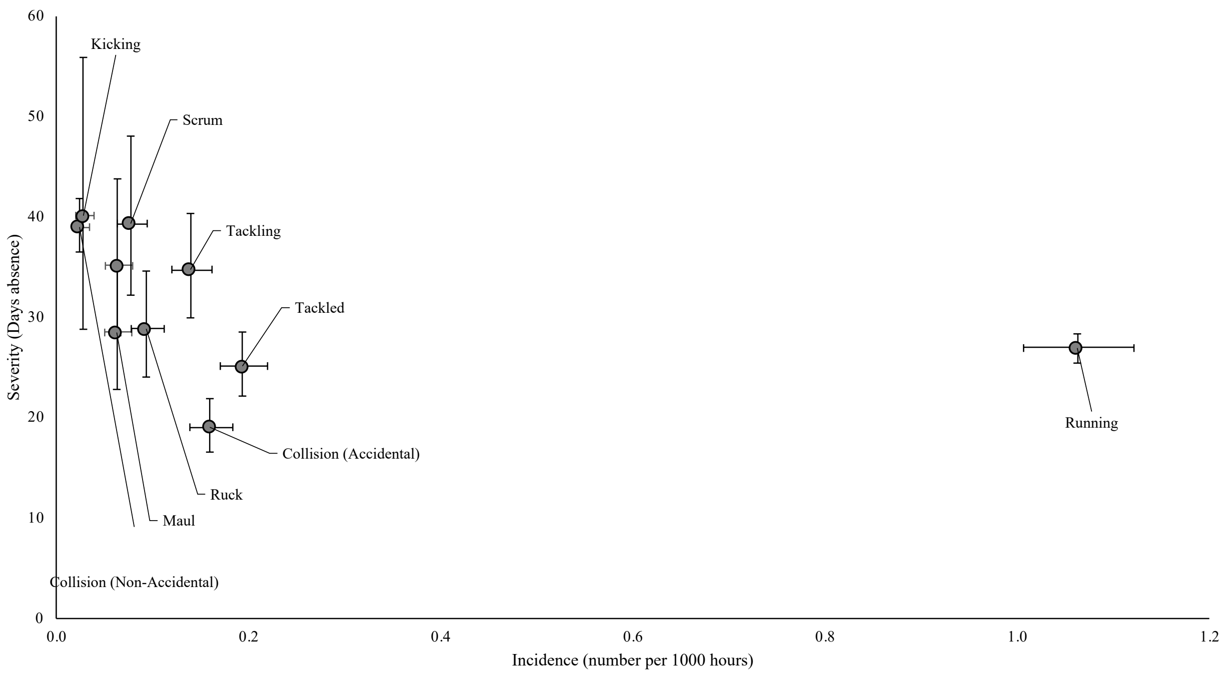

Figure 3.5: Training injury event for the seasons 2009-2010 to 2017-18. Injuries reported with the event "N/A" (<1%), "Other" (16%), "Unknown" (10%) are not included in the graph. Error bars represent 95% Confidence Intervals.

3.3.6 Injury Location

The most commonly injured body sites were the posterior thigh (incidence: 0.47/1000 player-hours; mean severity: 23 days) and the calf (incidence: 0.33/1000 player-hours; mean severity: 21 days): Figure 3.6. The knee was the body site with the most severe injuries (incidence: 0.29/1000 player-hours, mean severity: 48 days). The elbow (incidence: 0.03/1000 player-hours; mean severity: 44 days) and shoulder (incidence: 0.19/1000 player-hours; mean severity: 42 days) gave rise to injuries of similar severity, but were less frequent. Injuries to the head/face had an incidence of 0.12 /1000 player-hours and a mean severity of 15 days' absence. The incidence of concussion over the study period was 0.09/1000 player-hours with a mean severity of 14 days. The incidence of concussion rose from 0.01 per 1000 player-hours in the 3-season period 2007/08 to 2009/10 (three cases in three seasons) to 0.21 per 1000 player-hours in the 2017/18 season (32 cases in one season).

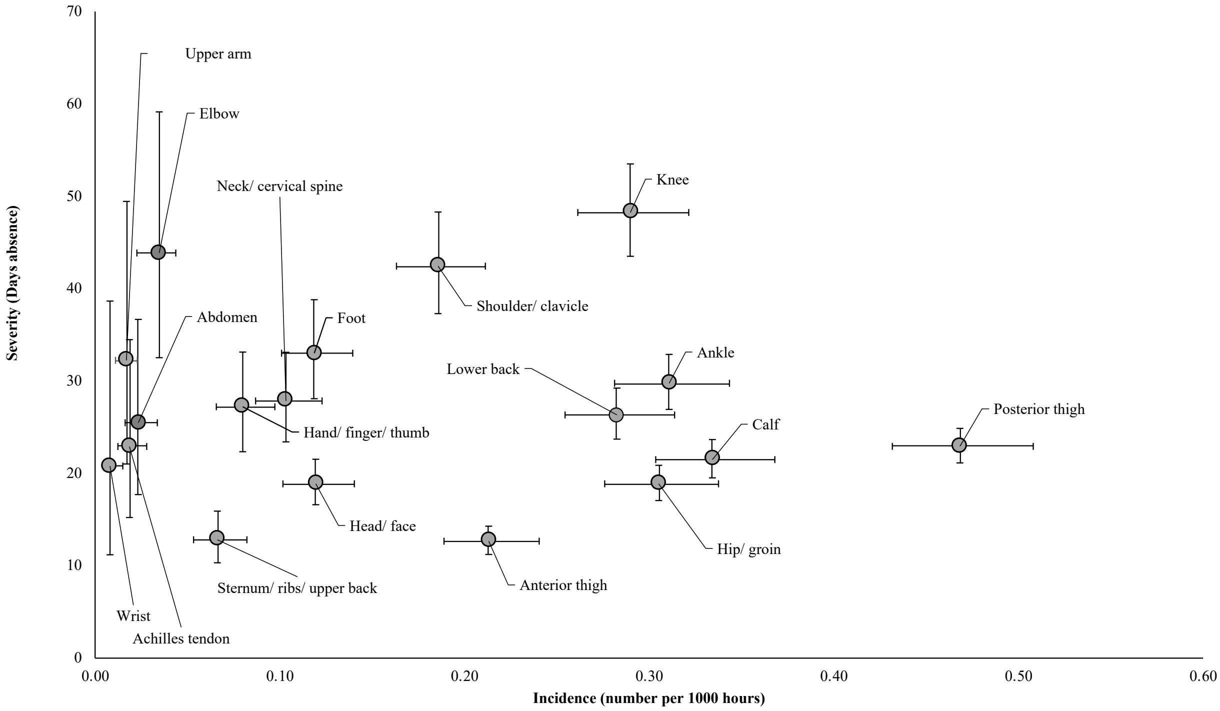

Figure 3.6: Injury burden as a function of body site for the seasons 2007-08 to 2017-18. The X-axis represents incidence (number per 1000 player-hours) while the Y-axis represents mean severity (days absence). Error bars represent 95% Confidence Intervals.

3.4 Discussion:

This study presents an in-depth summary of training patterns and training injuries over the seasons 2007/08 to 2017/18 in the top tier of English professional rugby. Over this period, neither the volume of training as a whole, nor the breakdown of the defined individual training categories, changed significantly. In contrast, within individual seasons, the volume and proportion of each training category changed substantially between pre-season and in-season periods. Pre-season training focussed on conditioning, whereas in-season focussed on non-contact rugby skills and gym-based conditioning. The overall incidence of training injury remained relatively stable, with full contact training injuries consistently the most frequent. There was a steady upwards trend over the 11 seasons for injury severity across all training categories. Injury burden followed a similar pattern to injury severity, as a function of the stable incidence and rising severity. Given the high number of injuries associated with running, the most common sites for injury were the posterior thigh, calf and ankle, while the most severe injuries occurred to the knee.

Over the course of the 11 seasons, the overall pattern of training remained stable (Figure 3.1A). Although the mean time spent training per player did not change, there was a rise in the total reported training volume between the 2007/08 (106,000 hours) and 2017/18 seasons (152,533). This rise in total volume, but no change in mean training time per player, reflects increasing squad sizes across Premiership clubs (mean squad size 2007: 45, mean squad size 2018: 60). To account for this change in squad size over time, the data presented in Figure 3.1 reflects mean time per player per week and, therefore, controls for squad size. It is important to recognise, however, that these are mean figures and each club will employ its own unique training methodology. Furthermore, the distribution of training volumes varies across the different stages of the season (Figure 3.1B). Unsurprisingly, June and May were the months with the lowest mean training volumes, as these months include the mandatory 5-week off-season for players and the majority of volume reported in May was provided by the small number of teams that make the playoff stages of domestic and European competitions. July and August comprise the main portion of the preseason period and these months had a mean training volume of 9 hrs per player per week (compared to the in-season period September to April of 6 hrs 6 mins per player per week).

Several previous papers have reported the structure of training in professional rugby union (Argus et al., 2009; Gannon et al., 2016; McLaren et al., 2017). The preseason training volumes reported in this study are comparable with those reported by Gannon et al. (2016) (7 hrs 24 mins) and McLaren et al. (2017) (8 hrs 48 mins to 9 hrs 24 mins). In a similar Premiership rugby sample (seasons 2002-03 and 2003-04), Brooks et al. (2008) reported a figure of 9 hrs 12 mins, supporting the conclusion that mean training duration for Premiership teams during preseason has, in fact, not changed over an even longer period of time.

During early pre-season (July), training was focused on athlete conditioning (gym-based conditioning, 3 hrs 48 mins; 3 hrs 18 mins, other conditioning). As the playing period of the season drew closer (August), the emphasis for training moved towards rugby skills but with a continued large proportion of time spent on gym-based conditioning. This corresponds with data from other studies that show a reduction in the volume of conditioning from pre-season to in-season (Argus et al., 2009; Gannon et al., 2016; Tee et al., 2016). The reduction in general conditioning sessions after pre-season is likely due to the adoption of individual prescription (Gannon et al., 2016). Interestingly, despite anecdotal evidence suggesting a greater emphasis on strength, power and size of players in recent years, there was no statistically significant changes seen in time spent performing gym-based conditioning over the 11-season period. This finding may indicate changes to the content and efficiency of training, with greater stimulus achieved through the same volume of training. In the present study, during the in-season period there was a weekly training volume of 6 hrs 6 mins per player per week, which is comparable with the 6 hrs 42 mins (first 20 weeks in-season) or 6 hrs 30 mins (final 11 weeks in-season) reported by Gannon et al. (2016) and the 6 hrs 18 mins reported by Brooks et al. (2008). The highest number of training injuries occurred during periods with the highest training volume (July and August); however, the incidence of injury did not change significantly during these periods.

Over the period 2007-08 to 2017-18 the incidence of training injuries remained stable with a mean of 2.6 per 1000 player-hours. In the Premiership over the period 2002-2004, Brooks et al. (2005b) reported an incidence of 2.0 per 1000 player-hours, while a study of Australian Super Rugby reported a value of 2.3 per 1000 player-hours during the 2014 season (Whitehouse, Orr, Fitzgerald, Harries and McLellan, 2016). In a 2013 meta-analysis, Williams et al. (2013) reported a comparable value of 3 injuries per 1000 player-hours of training for professional rugby. While the incidence of training injury is often not sub-divided by training category, Brooks et al. (2005b) reported a significantly higher incidence of injury in rugby skills training (2.1/1000 hours) compared to conditioning (1.6/1000 hours). The present study has demonstrated an incidence of injury during combined rugby skills training greater than that of conditioning (4.9 vs 2.5/1000 hours), with these figures notably higher than that reported by Brooks et al. (2005b). Although it is possible to control certain aspects of full contact training, when exposed to full contact training in a dynamic fast moving rugby environment, injuries can be considered more unpredictable than that of other training types. It is, therefore, unsurprising that the incidence rate in this training type is highest across all categories. While a reduction in the amount of training may seem a logical step to help reduce the number of training injuries, it is important to consider that a certain amount of contact training is likely necessary to not only prepare an athlete for the physical demands of the sport (Gabbett, 2016a) but also to be able to successfully complete the technical components of rugby skills such as tackling, rucking and mauling. Considering this, it could be argued that the length of time spent undertaking full contact training may in fact need to increase, with a greater exposure to technical contact based training such as that suggested by Hendricks and colleagues (2016; 2018). In the context of this dataset, it is not possible to establish how much, if any, of full contact training focused on tackle technique; however, given the evidence suggesting poor tackle technique is linked with higher match injury risk (Hendricks et al., 2015; Burger et al., 2016; Tucker et al., 2017; Cross et al., 2017), it is recommended that a portion of the focus should be on the technical aspects of the tackle.

Although injury incidence remained stable over the 11 seasons, injury severity rose almost every season. Given the potential for the mean value to be skewed by one or two long-term injuries, the median is also reported and this showed a similar upward trend over the 11-season period (Table 3.1). A similar trend has been reported for match injury severity (Kemp et al., 2019) and although the mechanisms for such a rise may stem from bigger contact events from stronger and faster players during games, in the training setting the trend for increased severity cannot be attributed solely to this high velocity contact as the increase in severity is evident across numerous session types. Therefore, the rise in injury severity may highlight a number of issues, including adoption of more conservative return to play protocols alongside the concurrent increase in squad sizes, or a genuine increase in the complexity of rugby union injuries. Though injury rates per training category have remained stable, the severity of these injuries has risen. Full contact training and gym-based conditioning displayed the greatest rise in mean severity (26 and 23 day rise on average between 2007/08 and 2017/18). Although gym-based conditioning exhibited the second largest rise over the time period, in 2017/18 conditioning (non-gym) exhibited the highest mean severity of injuries at 42 days, followed by full contact training at 40 days. Given the stability of training volume over time, the increase in injury severity may be a result of a change in other aspects of training, such as frequency, duration or intensity (Smith, 2003). As both the frequency and duration (overall volume) have not shown statistically significant changes, it is possible that changes in training intensity may have contributed to this rise in severity. This hypothesis cannot be examined with the data presented here, as training intensity was not captured, but it would be important to investigate this in future studies. Injury burden is considered a measure of overall injury risk as it accounts for both the incidence and severity of injury (Fuller, 2018). The present study demonstrates that the burden of injuries rose significantly from 2007/08 to 2015/16. During the 2016/17 and 2017/18 seasons this increase in burden was particularly evident, with this rise attributable to increases in both the incidence and severity of full contact training injuries. More detailed analysis of the composition and implementation of this category of training may also provide a greater understanding of the specific issues involved.

One further aspect to consider when evaluating the burden of injuries is the relative contribution of incidence and severity within the burden figure. Two teams exhibiting the same injury burden may not experience the same impact on player availability (Fuller, 2018). A team experiencing an injury burden resulting from high incidence but low severity injuries will be influenced by larger number of players unavailable for shorter periods of time, whereas a team experiencing an injury burden comprised of low incidence but high severity injuries will be affected by fewer players unavailable over longer periods. This difference would be more pronounced on a team if the players lost to injury in the low incidence high severity scenario are players that would have a significant effect on team performance. In the present study, the increase in burden is largely caused by rising severity; therefore, in practice, strategically planning for periods with reduced player availability in key positions is essential, with adjustments to squad sizes and strength and depth in those key roles recommended.

This study has demonstrated that the overall volume and composition of training, as well as the incidence of training injuries, in English professional players did not change over the last 11 seasons. However, the severity of injuries associated with training rose in all but two seasons between 2007 and 2018. One limitation of this study was that training intensity was not captured and, therefore, its potential impact on injury severity was not examined. Tools such as Global Positioning Systems (GPS) and session Rating of Perceived Exertion (Halson, 2014) may provide valuable, additional information in this context. A further limitation of this study is the lack of individual training volumes per player. These data were collected on a team basis, so individual contributions of injury status, player experience, player age, or other factors were not examined. This further supports the work of Cross et al., (2016b), which outlined the need for more long-term studies that assess individualised relationships between training load and injury risk in professional rugby. The practical implications of this study are evident for both practice and policy. In practice, this data can be used by clubs to identify differences between themselves and that of elite rugby union clubs in England, in both the volume of training completed as well as the injury patterns they see. Future work is needed to establish the exact nature, methodologies, intensity and composition of full contact training in particular, given its high incidence of injury. Furthermore, developing a greater understanding of the mechanisms driving the increase in injury severity is warranted to reduce the overall burden of injury from training. Capturing just over 1.5 million hours of training volume and 3,703 training injuries, this study provides the largest and most comprehensive view of training volume and training injury in professional rugby union. Although between season variation is apparent, the volume of training did not change between 2007/08 and 2017/18. Training injury incidence remained relatively stable, but the number of injuries associated with training is worthy of attention given that they are sustained in potentially more “controllable” conditions than those in match play. Improving understanding of evolving injury patterns in training and developing injury reduction strategies have the potential to positively impact upon on welfare of rugby participants as well as improving career longevity of those players involved at the professional level of the game.

CHAPTER 4

Risk and reward in the management of load: assessing the consequences of team-average training load prescription for both injury burden and team success.

4.1 Introduction:

The interaction between workload, injury and performance is central in the management of athletes in team sports. Despite this, the definition, monitoring and analysis of these metrics lacks consensus in both practical and research settings. In rugby union, “load” has been defined as “the total stressors and demands applied to the players” (Quarrie et al., 2016) while elsewhere, load has been defined, from a physical perspective only, as “the cumulative amount of stress placed on an individual from multiple training sessions and games over a period of time” (Windt and Gabbett, 2016). Similarly, there are numerous definitions for injury within and between different sports, varying from inclusive definitions such as any physical complaint (Fuller et al., 2007b) to more exclusive definitions such as those resulting in missed matches (Bathgate et al., 2002b). (Bathgate, Best, Craig and Jamieson, 2002a). Comparison between studies is challenging as differing definitions for each variable are likely to alter the nature of the relationship between variables (Hulin, 2017).

In both sport and research settings, “performance” can be either a behaviour or an outcome. Performance as a behaviour can be measured by sports statistics (Lazarus et al., 2017), key performance indictors (Drew, Raysmith and Charlton, 2017b), physical fitness improvements (Gabbett and Domrow, 2007), subjective coach ratings or physical performance outputs (Dupont et al., 2010). Performance as an outcome is often referred to as “sporting success” and can be measured by league position (Brooks et al., 2008), ranking systems (Drew et al., 2017b; Williams et al., 2015) or the winning of a specific game event or competition (Drew et al., 2017b).

Given the increasing use of scientific principles to monitor athletes there has been an increase in research exploring associations between injury, performance and load. Of these associations, the evidence surrounding injury and performance is clear, with low injury outcomes linked to improved team success in multiple sports (Drew et al., 2017b) including rugby union (Williams et al., 2015; Starling, 2019). Despite several studies and systematic reviews outlining the association between injury and load, current evidence is mixed with the nature of the relationship appearing to be affected by the sport being studied, load variables included in the analysis and injury definition used (Drew and Finch, 2016; Eckard et al., 2018). In the context of the load-performance relationship, although individual studies have demonstrated clear associations (Lazarus et al., 2017), a recent systematic review outlined little evidence for a link between external training load and performance (Fox, Stanton, Sargent, Wintour and Scanlan, 2018), while in rugby union training volume did not demonstrate an association with final league position (Brooks et al., 2008).

This novel study aims to establish whether associations between training load, injury burden and performance exist within rugby union. Where previous studies in this area have considered load, injury and performance separately, this study will explore how the three areas interact, addressing the need to find a balance between minimising injury risk while maximising performance potential.

4.2 Methods:

4.2.1 Participants

Data was collected from 13 Premiership clubs over the 2015/16 and 2016/17 seasons (10 clubs- 2 seasons, 3 clubs- one season). Individual load and injury data were captured for 433 and 569 players in each respective season(1002 player-seasons for 696 individual players). Injury data was collected as part of the Professional Rugby Injury Surveillance Project. Each player was provided with a participant information sheet and individual consent was obtained voluntarily. Players were only included if both injury and detailed training exposure was obtained. The study was approved by the University of Bath Research Ethics Approval Committee for Health (Ref no. 15/16 252).

4.2.2 Data Collection

Data on 24-hour time-loss injuries (Fuller et al., 2007c) was collected by club medical staff through an online data collection platform ("Rugby Squad"- The Sports Office UK Limited).. Training and match load data were captured for every session undertaken by each athlete using the session Rating of Perceived Exertion (sRPE) method (Foster et al., 2001). Each player was asked to rate the perceived exertion of each session on a scale of 1-10 (Borg et al., 1987) and this value was multiplied by the session's duration (in minutes) to give a sRPE load score for that session. This data was captured by sports science or conditioning staff in the clubs after the completion of a session to ensure a measure of load for the session as a whole was captured (Foster et al., 2001).

To calculate a weekly measure of performance, each week's game was given a match difficulty index (MDI) (Kelly and Coutts, 2007; Robertson and Joyce, 2017), which was multiplied by the outcome (points difference: positive or negative) of the game being measured. To calculate the MDI for a given match, three fixed factors (opposition rank in the previous season, match location: home/ away, days turnaround between fixtures) and 6 dynamic factors (opposition rank in the current season, difference in league positions, team form, number of team changes in previous week, number of team changes in past 4 weeks and number of players in 1st season of career) are suggested. However, due to the complexity involved in the final 3 dynamic factors on a league wide scale only the first six factors were used in this study (3 fixed and 3 dynamic). Using these six factors, binary logistic regression, with a win (1) or loss (0) used as the dependent variable, was utilised, with drawn games excluded from analysis (11 over two seasons) (Robertson and Joyce, 2017). Taking the Logit probability value of a win, subtracted from 1 and multiplied by 10 provided each game with an arbitrary unit value of 1-10, with 1 representing an easier match than an MDI of 10. To give a performance score for each week, the MDI was multiplied by the points difference in the game. If the outcome of the game was a loss, the inverse of the MDI was taken so that a loss against a team with a high MDI (less chance of winning) was given a better performance score than that of a loss against a team with a low MDI (higher chance of winning). To provide a simple metric for analysing European games, Champions Cup matches (the highest tier of European rugby) were given the average MDIs for playing a team finishing in the top 6 teams in the Premiership table in the previous season, either home or away. Challenge Cup (second tier) games were given as the average MDI for playing a team from teams 7-12 in the previous season (home and away). This meant that there was a standard MDI for all home and away games for Champions and Challenge Cup fixtures for the two respective seasons.

In any given week, only training and injury data for players selected for the match day 23 (MD23) were included in the study. The weekly injury value assigned to each team was that of injury burden (number of days absent per 1000 hours exposure), which accounts for both injury incidence and severity (Brooks et al., 2005a). The injury burden in the MD23 group each week represents predominantly match injury burden, as well as any burden from low severity training injuries occurring early in the week, as any serious injury burden within that week would rule a player out for selection in that week’s fixture. This, therefore, means that injury burden in this study is likely to have a greater effect on in-game tactics and to a lesser extent preparation in any given week.

4.2.3 Data Analysis

Individual injury and load data were collated to provide a weekly value for each team over the course of the season. Average weekly loads, average smoothed chronic load and the average acute: chronic workload ratio (ACWR: average acute load/ average smoothed load) were calculated for each week. The smoothed loads were calculated using an exponentially weighted 4 week average as described by Williams et al (Williams et al., 2016b). Z-scores for each of the average and chronic loads were calculated to standardise training weeks within each team. As the majority of competitive fixtures occur between Friday and Sunday, each new weekly value began on a Monday and, therefore, the mean scores for each week include one game exposure. All statistical analysis was performed using R Studio (RStudio, Version 1.0.136). All modelling was undertaken using the "*lme4*" package (Bates et al., 2018) and 95% confidence intervals for marginal means were produced using a bootstrapping method via the "*BootMer*" package (Bates et al., 2018). Linear mixed models were used with load measures (acute, smoothed, acute: chronic ratio), and performance (arbitrary score) as the independent and dependent variables, respectively. The distribution of the injury burden demonstrated clear negative skew to the left and, therefore, generalised linear mixed models were used with a Gamma distribution and log link function, in any case where the dependent variable was injury burden. "Club" was included as a random effect in the models to account for differences between clubs. Player availability (as a percentage) and squad size were modelled against performance to identify whether inclusion in the linear mixed models would moderate the association between main outcome variables. Quadratic terms were included in each separate model to identify whether non-linear tendencies were apparent. Variables showing non-linearity were split into quartiles of equal sample size to assess the effect on outcome variables, while variables demonstrating linear relationships only were evaluated per 2 SD change in the predictor (Hopkins, Marshall, Batterham and Hanin, 2009). Magnitude based inferences (MBIs) were used to assess the importance of the model estimates, which are based on effect size and corresponding confidence intervals (CIs) in relation to a smallest worthwhile change. The smallest worthwhile change was calculated as 0.2 of the SD in the dependent variables in the models (injury burden = 21.3 units and performance = 11.7 units). Unclear effects were reported if 90% CIs crossed both the threshold for harm and benefit by 5% (Hopkins et al., 2009). Should the effect be clear, it can be termed as beneficial, harmful or trivial (less than the smallest worthwhile change), with the strength of the effect expressed using a qualitative probabilistic term using the following thresholds: <0.5%, most unlikely; 0.5-5%, very unlikely; 5-25%, unlikely; 25-75% possibly; 75-95%, likely; 95-99.5%, very likely; >99.5%, most likely (Hopkins et al., 2009).

4.3 Results:

The mean squad size was 57 (±5) players, while mean percentage availability was 85% (±7%), meaning on average, teams had 48 players to select from on a weekly basis (Table 4.1). The mean weekly injury burden was 84 (±106) days, while the mean performance score was 5 (±58) arbitrary units (AU).

Table 4.1: Descriptive statistics of training, injury and performance measures.

Measure	Mean ± SD
Weekly Load	2032 ± 629 AU
Smoothed Load	1943 ± 539 AU
Acute: chronic ratio	0.96 ± 0.30
Injury Burden	84 ±106 days
Player Availability	85 ± 7%
Squad Size	57 ± 5 players

4.3.1 Performance, squad size and player availability.

A 2 SD change in squad size (10 players) was associated with a 6 unit increase in performance while a 2 SD change in player availability (14%) was associated with a 7 arbitrary unit increase in performance. Whilst these indicate that a larger squad size and greater percentage availability were associated with improved performance, both were considered "*likely trivial*" and were, therefore, excluded from further analysis.

4.3.2 Injury burden and performance

The relationship between injury burden and performance displayed non-linear tendencies (p= 0.09) and, therefore, injury burden was split into quartiles for analysis (Low: 0-12 days, moderate-low: 13-47 days, moderate-high: 48-117 and high: 118-869). Moving from a low to high injury burden was associated with an 18 unit decrease in performance and was, therefore, deemed greater than the smallest worthwhile change and "*Likely Harmful*" (p= 0.007: Figure 4.1). When moving from the low to low-moderate or high-moderate categories, only "*Possibly Trivial*" 7 and 9 unit changes in performance were seen.

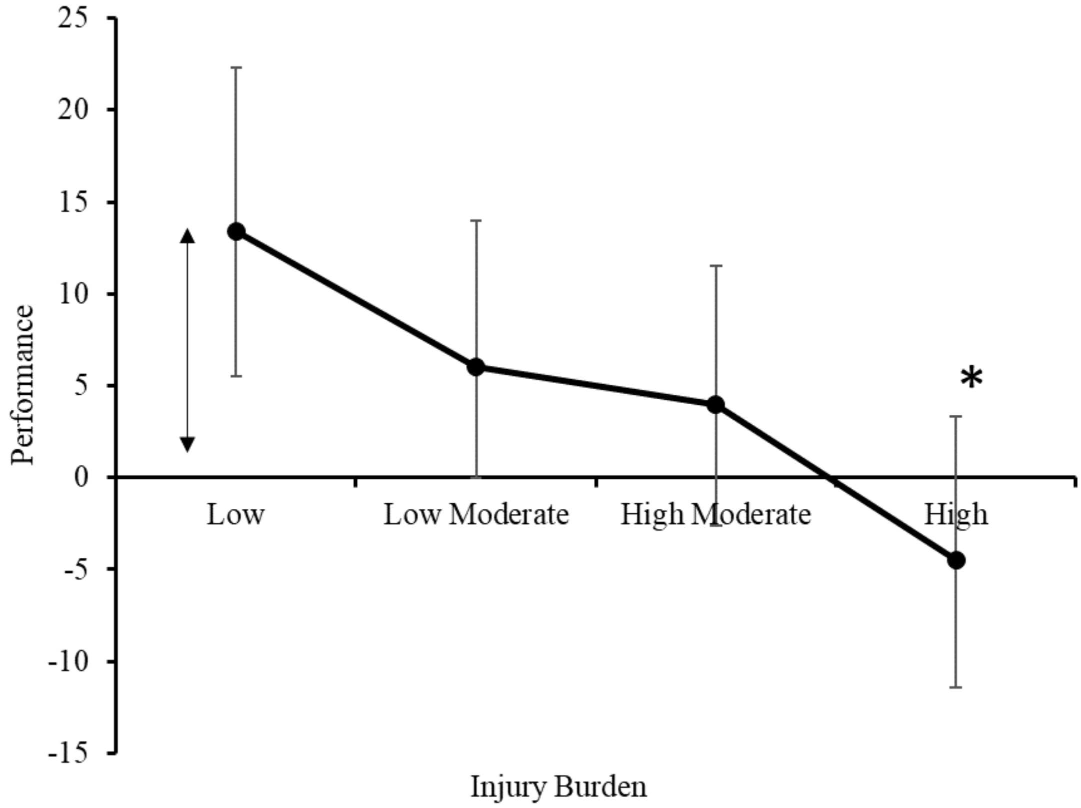

Figure 4.1: The association between performance and differing levels of injury burden. Confidence intervals= 95%. Asterisk indicates clear difference between reference group and group of interest. Black arrow indicates smallest worthwhile change in performance = 11.7 units

(in each figure, the black arrow is anchored on the first value on the graph, with the arrow in the either above or below that first point in the same direction of the relationship)

4.3.3 Training load and performance

Average weekly load and the acute: chronic ratio displayed only linear tendencies (p= 0.243) and were, therefore, analysed per 2 SD change. The smoothed load displayed non-linear characteristics and was, therefore, analysed in quartiles (Figure 4.2). A 2 SD change in average load and the acute: chronic workload ratio were associated with "*likely trivial*" 6 unit increases and 3 unit decreases in performance. Moving from a low to mod-low, low to mod-high and low to high category of smoothed load were all associated with "*likely trivial*" changes in performance (5 unit decrease, 0.1 unit increase and 6 unit increase respectively).

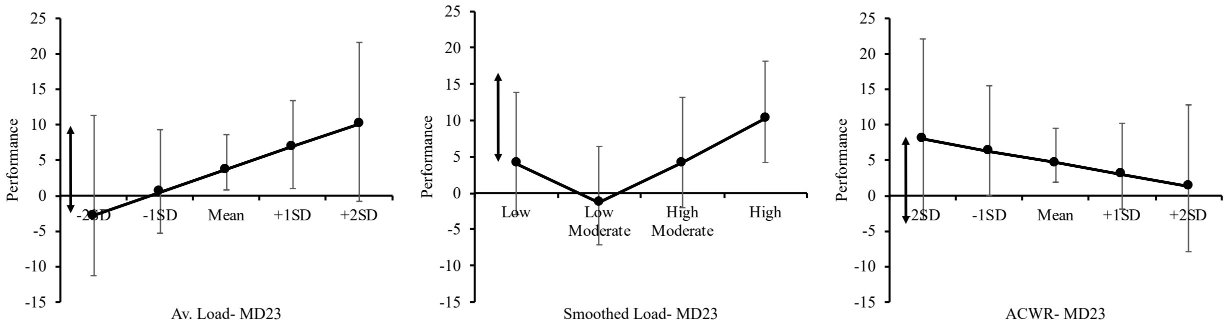

Figure 4.2: Association between training load and performance. (Confidence intervals= 95%, black arrow indicates smallest worthwhile change in performance = 11.7 units).

4.3.4 Training load and injury burden

Weekly load and smoothed load displayed no non-linear properties (p=0.73 and p=0.36 respectively) and were, therefore, analysed per 2 SD change, whereas a non-linear relationship was found in the ACWR variable and was, therefore, analysed using the same quartiles (p<0.01). Changes in the acute and smoothed load variables were associated with only trivial 15 and 20 unit changes in injury burden (Figure 4.3A and 4.3B). The ACWR variable demonstrated a "Possibly Harmful" 25 unit increase in injury burden (p<0.01: Figure 4.3C).

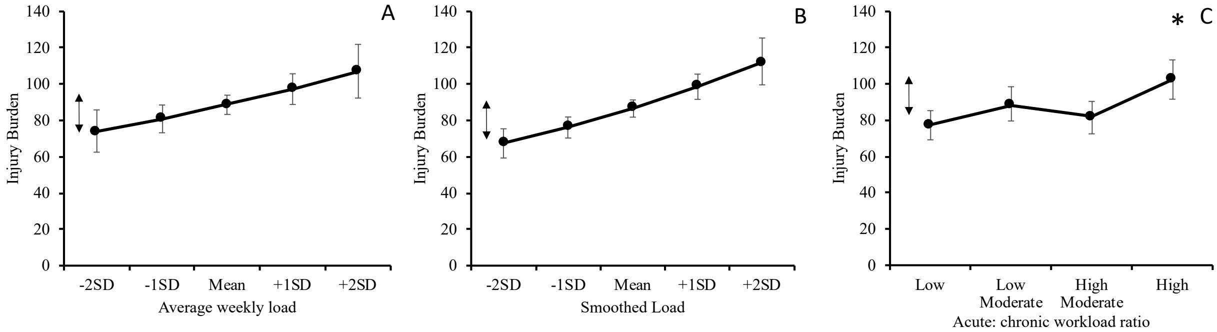

Figure 4.3: Association between training load and injury burden: A: Average weekly (acute load), B: Smoothed load and C: Acute: chronic workload ratio. (Confidence intervals= 95%, Asterisk indicates clear difference between reference group and group of interest. black arrow indicates smallest worthwhile change in injury burden = 21.3 units).

4.3.5 Training load and performance (at differing levels of injury burden)

There was a clear main effect of injury burden on performance (with lower levels of injury burden associated with improved performance), however, there was no clear interaction effect between load and injury. Despite no statistically clear interactions, visual inspection of Figure 4.4C suggests that an interaction exists between the three levels of injury burden and the ACWR load variable.

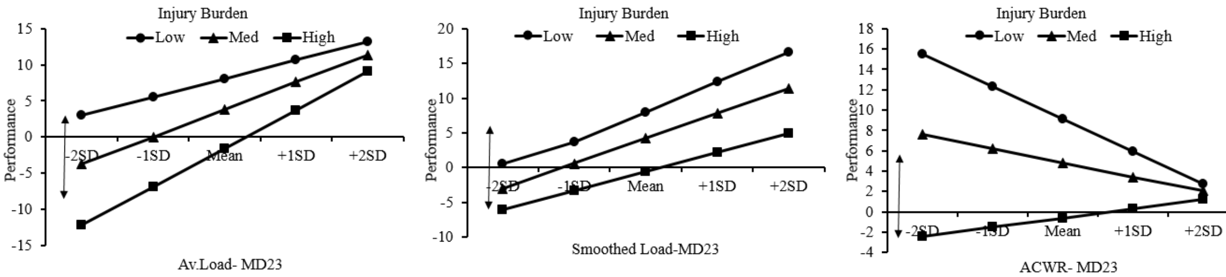

Figure 4.4: Association between training load (x-axis) and performance (y-axis) at three levels of injury burden (3 lines) for average load, smoothed load and ACWR. (Black arrow indicates smallest worthwhile change in performance = 11.7 units)

4.4 Discussion:

The study provides an overview of the associations between team average training load, injury burden and performance in rugby union. Injury burden was negatively associated with performance, while training load measures (acute, chronic and ACWR) displayed only trivial associations with performance. Of the training load measures assessed, only the acute: chronic workload variable was associated with injury burden. When accounting for injury burden, there was no significant interaction effect with load on performance, meaning that the effect of load on performance is not dependant on the level of injury burden. Despite this, across all three measures of training load, the lowest injury burden category was associated with the highest performance. To understand the role of squad size and player availability in rugby union, these measures were assessed to identify whether either would contribute to an enhanced likelihood of success. The change in performance (6 performance units) associated with a 2 SD change in squad size did not reach the threshold for the smallest worthwhile change, indicating that increasing squad size by 10 players would not be associated with a meaningful change in performance, if player management was to remain unchanged. Similarly, the change in performance associated with a 2SD change in player availability means that a 14% improvement in availability does not lead to a meaningful change in performance (7 unit). It is important to recognise, however, that this analysis did not account for the players to whom the injuries in the study were sustained and their relative importance within the squad, which is likely to be influential in the effect of player availability on performance. Further to this, within the data representing player availability, a number of players will be included that spend the majority of the time available for selection, as they rarely play top level fixtures and consequently do not experience exposure to higher injury risk in match play. This is exemplified by Quarrie et al., (2013) who report that 40% of all Premiership players play less than 548 minutes (7 games) per season. Further analysis in this study was performed on the players involved in fixtures on a weekly basis, which may represent a better assessment of high-quality player availability than player availability across the squad as a whole.

A negative association between injury burden and team success has been shown previously in rugby union (Williams et al., 2015) as well as several other sports (Drew et al., 2017b). In Williams et al (2015), the injury and performance metrics used were injury burden (injury incidence x mean severity), league points tally and season average Eurorugby Club Ranking (ECR). Williams et al., (2015) found clear negative associations between injury burden and team success on a seasonal basis, and the present study supported this finding on a weekly basis, with a high injury burden associated with a "*Likely Harmful*" 18 unit decrease in performance (Figure 4.1). To contextualise what this may mean for performance in Premiership or European competitions, minimising injury burden (to less than 12 days) within a week increases the likelihood of performance by 18 units, which for a challenging fixture could be the difference between winning or losing the game (e.g., going from a 1 point loss to 2 point win in a match of match difficulty index (MDI) of 9). This change of 18 units could also represent the difference in a team achieving a bonus point or not in a game (e.g., scoring a try in the last minutes of a game with a MDI of 2.5). While the importance of this 18 unit change in performance may not always be important in the context of that game, these changes could result in an extra 3 league points at the end of the season for a team, which has previously been reported as a meaningful change in points tally as the difference between playoff (4th vs 5th) positions and European qualification (6th

vs 7th) positions (Williams et al., 2015). This finding supports the benefit of minimising injury risk.

Changes in acute, smoothed and acute: chronic workload ratio variables were each found to show trivial associations with performance. These findings do not support the work of Lazarus et al., (2017) which found that performance was highest when near the mean or ~1 SD below the mean. The trend towards a lower than average load value contributing to a greater performance score was seen with the acute: chronic measure, however, the opposite was seen with the acute load measure, whereby a greater than average value was seen to be associated with a higher performance score; it must be recognised, however, that these findings were not clearly beneficial. The lack of clear findings may be due to the lack of sensitivity of the performance and load measures. The absence of consistent associations between training load and performance prevents any meaningful recommendations for practice, reflecting the conclusions of a recent systematic review across team sports, which also identified inconsistencies in this relationship (Fox et al., 2018).

When assessing training load and injury burden, 2 SD changes in acute and smoothed loads were associated with only trivial changes in injury burden. Despite this, it was found that a high ACWR was associated with a "*Possibly Harmful*" 24.9 unit increase in injury burden ($p<0.01$). This finding appears to support the concept of a large weekly load relative to chronic load being a "spike", which has been shown to be associated with injury risk in rugby union (Cross, Williams, Trewartha, Kemp and Stokes, 2016a), soccer (Malone et al., 2017b), cricket (Hulin, 2014) and several other sports (Drew and Finch, 2016). Overall the findings of the analysis of training load and injury burden indicate that, when considering team averages, the acute: chronic metric has a greater impact than either acute or chronic load in isolation. Further to this, increasing ACWR values showed negative, yet trivial, findings for performance, with high ACWR values representing the lowest performance. While these findings are unclear, they suggest that for both minimising injury burden and increasing likelihood of team success, managing players to avoid large rises in the overall team average ACWR may be important.

This study is one of the first to consider the influence of training load on both performance and injury burden simultaneously and as such the analysis of the effect of the three training load variables on performance score at three levels of injury burden was completed (Figure 4.4). As expected, when looking at each of the three training load measures, the lowest level of injury burden displayed the highest performance outcome in all cases, while the highest injury burden displayed the lowest performance values. Although no significant interaction effect was found, when using the ACWR training load variable, visual inspection of the different slopes associated with each injury burden level suggests that with greater sensitivity of load, performance and injury measures, the effect of load on performance may be moderated by injury burden.

One of the major difficulties associated with this type of research is the ability to define performance. One of the limitations of the current study may be the lack of sensitivity of the performance marker used. While match difficulty indices have previously been used (Robertson and Joyce, 2017), the use of this metric alongside weekly points difference has not previously been used as a performance measure. Without the level of performance indicators used in Bennett et al (Bennett, Bezodis, Shearer, Locke and Kilduff, 2019), the match difficulty index was used to account for both difficulty of game as well as the outcome. Limitations associated with the performance measure may explain the lack of a relationship between training load and performance and improvements to these measures would potentially improve the strength of the associations between the variables. Another limitation with potential for improvement in further work would be the individualisation of the training load and injury data. Other avenues for future work include distinguishing between match preparation burden and match burden itself to identify whether injury burden associated with the build-up to a game is more disruptive than that of burden associated with a game itself.

This study demonstrates a clear association between training load and injury risk at the team level, and supports the well-established link between injury and performance. Although associations between training load and performance were not clear, this study outlines the need to build measures of performance into research examining training load and injury.

CHAPTER 5

Complexities of injuries risk management using training load data (Part 1): Assessing metric calculation for risk mitigation

5. 1 Introduction:

Modern day professional sport has adapted in recent years to accommodate the growing commercial demands of television by adopting more heavily congested fixture schedules (Soligard et al., 2016). Consequently, the importance of managing player training load between fixtures is growing, capturing the attention of international sports governing bodies including the International Olympic Committee (Soligard et al., 2016) and World Rugby (Quarrie et al., 2016). Recent evidence suggests that improper prescription of training load can negatively influence injury risk (Drew and Finch, 2016; Jones et al., 2017; Eckard et al., 2018), which in turn is associated with negative consequences for team success (Hägglund et al., 2013; Williams et al., 2015; Drew et al., 2017c). To overcome this, practitioners across sport have taken a more scientific approach to training load management (Halson, 2014). While the use of evidence-based training load prescription may represent a gold standard approach to managing athletes, the fast-paced nature of elite sport often requires practitioners to act on intuition and implement methodologies deemed to be ecologically valid, while research aims to scientifically validate these processes through more rigorous investigation, as is the aim for the present study.

Training load can be defined as "the cumulative amount of stress placed on an individual from multiple training sessions and games over a period of time" (Gabbett et al., 2014) and can be measured using a number of internal (e.g., session Rating of Perceived Exertion-sRPE) or external (e.g., Global Positioning Systems- GPS) load measurement tools (Halson, 2014). Using the collected training load data of choice, a number of data aggregation methods are possible, including the use of acute and chronic time periods as well as ratio values combining the two (the acute:chronic workload ratio) (Gabbett, 2016a). The acute:chronic workload ratio is a popular tool that captures both the 'fitness' and 'fatigue' status of an athlete with the aim of minimising injury risk, while maximising performance potential (Gabbett, 2016a). Originally termed "training stress balance", a chronic (28 days rolling average) value is divided by an acute (7 day) load to produce a ratio, with values of over 1 representing a higher acute load relative to the 4 week average, and values under 1 representing a lower acute load relative to the last 4 weeks (Hulin et al., 2014; Gabbett, 2016a). When calculating such measures, a number of considerations should be accounted for including differing acute and chronic time periods, averaging methods and mathematical coupling. Since the original use of 7 and 28 day acute and chronic time periods, a number of time periods have been suggested ranging from 2-14 days (acute) and 12-56 days (chronic) (Carey et al., 2017a; Stares et al., 2018). Each of these studies reported not only different optimal time windows for capturing acute and chronic load in the same sport, but also different values based on the GPS metric being used, hinting at the potential complexity of assigning optimal time windows in training load measurement.

When calculating acute:chronic workload metrics, the use of ratios calculated using rolling averages has previously been reported as associated with injury risk (Hulin et al., 2014; Gabbett, 2016a; Drew et al., 2017a). However, rolling averages have been criticised for not accounting for the physiological effects of fitness and fatigue, which are likely to decay at different rates (Menaspa, 2017; Williams et al., 2016b). To overcome this issue, Williams et al. (2016b) proposed the use of exponentially weighted moving averages (EWMA: (Hunter, 1986)), which allow for the decay of older values in a time series at different rates, pre-determined by the practitioner (unlike a rolling average which assigns equal value to each daily load in the specified time-frame). The use of the EWMA method has since been demonstrated as more sensitive indicator of injury likelihood than that of rolling averages, with a much higher degree of variance explained using the former method (Murray et al., 2017a; Esmaeili et al., 2018). While it appears that the use of the EWMA method may offer a superior measure for managing injury risk, given the previous evidence suggesting a relationship between rolling averages and injury risk in other rugby codes (Hulin et al., 2016a; Hulin et al., 2016b), a comparison of the two methodologies is warranted.

The most commonly used method for calculating the acute: chronic workload ratio involves the inclusion of the 7-day acute period within the 28-day chronic period. Despite this being widely used, it is recognised that mathematical coupling occurs when the numerator in a ratio makes up a substantial portion of the denominator, as is the case with the acute:chronic workload ratio (Lolli et al., 2017). This coupling can lead to research inferences and monitoring practices that may be compromised by spurious correlations (Lolli et al., 2017). While the existence of mathematical coupling within the acute:chronic workload ratio is indeed present, Windt and Gabbett (2018) outline how the acute:chronic workload ratio essentially reports how much of the chronic load is made up by the acute load, with values ranging from zero to four possible. Until now, no study has examined the differences between coupled and uncoupled acute:chronic workload ratios and their respective associations with injury risk.

In the context of professional rugby union, only two previous studies have examined the relationship between training load and injury risk. The first used only a summed volume in its comparison (Brooks et al., 2008), while the more recent work from Cross et al. used the initially proposed 7 to 28 rolling average acute:chronic workload ratio. In this study, unclear findings were reported for the association between 2 SD changes in the acute:chronic measure and injury risk, stating a need for further data to explore this measure in greater detail. Further to this, in a review of load management principles for rugby union, Quarrie et al. (2016) outlined the need for research projects of a larger scale to make evidence-based decisions regarding player load and welfare. Given the methodological advances in athlete monitoring in recent years, as well as the conflicting evidence for the use of different analytical approaches to this type of data, a large-scale study of the acute:chronic workload ratio in the context of rugby union is required to establish methods of best practice. The aim of this study, therefore, is to establish the time periods and calculation methods (rolling vs exponentially weighted, coupled vs uncoupled) which are most prudent for managing injury risk in rugby union. This study will also represent the largest study of its type globally, with a league wide data collection being undertaken to capture the importance of between club variation, which has previously been unaccounted for in single-team studies.

5.2 Methods:

5.2.1 Participants

Data were captured from 13 Premiership clubs over the 2015-16 and 2016-17 seasons (10 clubs for two seasons, three clubs for one season). Four hundred and thirty-three and 569 players were recruited in the two seasons respectively, with 1002 total player-seasons included in the dataset (696 unique players). Injury data were collected as part of the Professional Rugby Injury Surveillance Project and as such, each player was provided with a participant information sheet and individual consent was obtained voluntarily. Players were only included if both medical injury data as well as training load data were collected, with a minimum of 100 consecutive days of training data required for inclusion (41 players excluded). The study was approved by the University of Bath Research Ethics Approval Committee for Health (Ref no. 15/16 252).

5.2.2 Procedures

In this study, time-loss injuries were defined as "an injury that results in a player being unable to take a full part in future rugby training or match play" (Fuller et al., 2007c) with all match and training injuries collected by the medical staff within each club. Training load data were collected by members of the conditioning staff and was captured using the session Rating of Perceived Exertion (sRPE) method (Foster et al., 2001). This measure was chosen for its ease in use, applicability to multiple session types, and widespread use across professional rugby clubs (Sweet, Foster, McGuigan and Brice, 2004; Comyns and Hannon, 2018). The inclusion of 13 clubs across two seasons also dictated the use of a measure that was universally captured using the same methods, while the scientific validity and reliability of the measure has previously been demonstrated in multiple sports (Haddad et al., 2017). Within 30 minutes after the completion of all sessions, players were asked to rate the global intensity of the session using a Borg CR-10 scale (Borg), which was then multiplied by the session's length in minutes to produce a single arbitrary unit (AU) load measure for the session (Foster et al., 2001). Players, where possible, were blinded to the score of fellow athletes to reduce the potential for bias (Comyns and Hannon, 2018). Players with missing data were followed up within the clubs to obtain an RPE score or were assigned a positional average for that session should follow-up prove unsuccessful. Data were collected daily and sent monthly to the lead researcher in the format collected by the club. The lead researcher then took this data and collated it in a standard format using Microsoft Excel. On completion of the season, the datasets were collated into one file, ensuring each player had a training load value for each day, irrespective of whether they trained or not i.e. "0" for a day without training or matchplay. Match minutes for each player across the period were obtained through an online platform ("Elitehub", RFU, 2019) and for each match day a player's match load was calculated as the number of minutes played multiplied by an RPE of 10, as it was assumed that maximal effort was given by players. Data were graphed using the package *ggplot* in RStudio (version 1.1.463) to identify players with a low number of data points. These players were then followed up individually and removed if a period of 100 consecutive days of load data were provided. Injury data were linked with the training load data, with a binary 1 "Injured", 0 "Not injured" system used.

5.2.3 Data Analysis

On collation of the final training load dataset, the file was imported into MatLab (MathWorks®) to produce each of the data combinations required for analysis. For each daily load value per player, 216 derivative training load values were calculated. These were:

- Coupled data
    - Rolling averages **(8 measures)**
        - Acute values (3,5,7,9 days)
        - Chronic values (14,21,28,35 days)
    - Exponentially weighted moving averages **(8 measures)**
        - Acute values (3,5,7,9 days)
        - Chronic values (14,21,28,35 days)
- Uncoupled data
    - Rolling Averages **(20 measures)**
        - Acute values (3,5,7,9 days)
        - Chronic values
            - (14,21,28,35 days)- using a 3-day acute period to uncouple acute from chronic
            - (14,21,28,35 days)- using a 5-day acute period to uncouple acute from chronic
            - (14,21,28,35 days)- using a 7-day acute period to uncouple acute from chronic
            - (14,21,28,35 days)- using a 9-day acute period to uncouple acute from chronic

- Exponentially weighted moving averages **(20 measures)**
  - Acute values (3,5,7,9 days)
  - Chronic values
    - (14,21,28,35 days)- using a 3-day acute period to uncouple acute from chronic
    - (14,21,28,35 days)- using a 5-day acute period to uncouple acute from chronic
    - (14,21,28,35 days)- using a 7-day acute period to uncouple acute from chronic
    - (14,21,28,35 days)- using a 9-day acute period to uncouple acute from chronic

- Acute:chronic workload ratio interactions
  - 3:14, 3:21, 3:28, 3:35
  - 5:14, 5:21, 5:28, 5:35
  - 7:14, 7:21, 7:28, 7:35
  - 9:14, 9:21, 9:28, 9:35
    - Calculated for Coupled- Rolling and EWMA **(32 measures)**
    - Calculated for Uncoupled- Rolling and EWMA **(128 measures)**

These data were exported from Matlab and imported to RStudio as a text file for analysis. Fifteen different data subsets were created, one for each season (including all clubs) and 13 individual club subsets. Using training load on the day of injury can lead to unusually low load values if the player is unable to complete the full scheduled session due to the injury, and, therefore, a one-day injury lead was calculated to move the injury dates back by one day to correspond with the load value on the morning of the day of injury. This was done to assess injury in a prospective way with training load data up until the day of injury, and not retrospectively once the injury has already occurred. For this analysis, all injury types were included, both contact and non-contact. Generalised linear mixed models were used to assess the relationship between each of the acute:chronic workload ratio metrics and injury risk, using the "*lme4*" package in RStudio (Bates et al., 2018). Repeated measures were accounted for using a random effect for player identification number (Equation 5.1). Model fit was assessed using the Akaike Information Criterion (AIC) with a smaller AIC value representing a greater model fit. AIC summaries were exported for each model to assess the time periods and calculation methods which produced the lowest AIC values. In the context of AIC, not only is the lowest value deemed important but the relative value over the other set of models considered (Burnham and Anderson, 1998). As the difference between the lowest and next model becomes larger, this represents less support for the next model being the best available model, with differences of > 10 representing essentially no empirical support for the model compared with the lowest choice (Burnham and Anderson, 1998).

As per the recommendations set out in Burnham and Anderson (1998), differences between training load models will be compared using the following guidelines:

Level of empirical support for use of one model compared to the lowest:

- Difference in AIC values of 0-2: “Substantial”
- Difference in AIC values of 4-7: “Considerably Less”
- Difference in AIC values of >10: “Essentially None”

To validate the findings of the investigations using AIC value with other previously used measures of model selection, Area Under the Curve (AUC) was also assessed, with a higher AUC value representing a better performing model (Colby et al., 2017).

Equation 5.1

$$\gamma ij = \beta_0 + \beta_{1x1ij} + \beta_{2x2ij} + \ldots + u_j + e_{ij}$$

5.3 Results:

Over the study period 129,448 training load values were collected (excluding days off, which had a load value of 0), while 1718 injuries were recorded. Across each of the 13 clubs, widespread variation existed as to the training load values that represented the lowest AIC values and, therefore, best fitting model (Figure 5.1). Table 5.1 portrays the best available model fit for each club, indicated by the lowest AIC score, again demonstrating widespread variation between different clubs.

Table 5.1: The best available acute:chronic workload ratio calculation for each club (rows 1-13) and when all data were analysed together (row 14).

Club	Method	Coupling	Acute	Chronic
Club 1	EWMA	Coupled	3	14
Club 2	RA	Coupled	7	14
Club 3	RA	Coupled	3	14
Club 4	EWMA	Coupled	3	14
Club 5	RA	Coupled	3	14
Club 6	RA	Coupled	9	14
Club 7	EWMA	Coupled	3	35
Club 8	EWMA	Coupled	9	21
Club 9	EWMA	Coupled	3	35
Club 10	EWMA	Coupled	3	21
Club 11	EWMA	Coupled	3	14
Club 12	RA	Coupled	3	14
Club 13	EWMA	Coupled	5	14
All clubs combined	**EWMA**	**Coupled**	**3**	**14**

			Coupled				Uncoupled			
			14	21	28	35	14	21	28	35
Club 1	RA_INJ	3	2106	2117	2129	2136	2122	2129	2136	2141
		5	2122	2127	2134	2139	2125	2132	2137	2141
		7	2116	2122	2131	2133	2124	2132	2137	2141
		9	2106	2114	2119	2123	2124	2132	2137	2141
	EWMA_INJ	3	2043	2070	2080	2077	2115	2114	2118	2121
		5	2060	2079	2086	2084	2100	2104	2109	2112
		7	2070	2083	2087	2085	2090	2095	2101	2106
		9	2078	2086	2087	2085	2084	2089	2096	2102
			14	21	28	35	14	21	28	35
Club 2	RA_INJ	3	1921	1932	1935	1947	1922	1922	1928	1943
		5	1920	1930	1936	1950	1921	1922	1927	1937
		7	1920	1928	1935	1949	1923	1921	1928	1942
		9	1927	1934	1938	1951	1926	1925	1932	1945
	EWMA_INJ	3	1937	1941	1944	1945	1970	1969	1968	1968
		5	1934	1938	1941	1944	1969	1969	1968	1968
		7	1940	1942	1944	1945	1966	1966	1966	1965
		9	1948	1946	1947	1948	1965	1965	1964	1963
			14	21	28	35	14	21	28	35
Club 3	RA_INJ	3	1318	1341	1351	1365	1342	1350	1363	1366
		5	1342	1342	1346	1359	1345	1348	1362	1363
		7	1344	1347	1351	1364	1345	1349	1363	1365
		9	1344	1348	1350	1364	1344	1350	1363	1366
	EWMA_INJ	3	1357	1367	1373	1375	1370	1366	1363	1365
		5	1347	1360	1368	1372	1374	1372	1364	1363
		7	1354	1362	1368	1371	1373	1372	1365	1362
		9	1359	1364	1368	1369	1372	1371	1364	1361
			14	21	28	35	14	21	28	35
Club 4	RA_INJ	3	2350	2339	2340	2340	2341	2342	2338	2332
		5	2348	2348	2349	2344	2337	2342	2339	2337
		7	2348	2354	2356	2357	2336	2344	2344	2339
		9	2352	2362	2362	2359	2335	2352	2348	2341
	EWMA_INJ	3	2276	2277	2280	2285	2352	2346	2349	2351
		5	2293	2292	2296	2301	2350	2351	2353	2354
		7	2308	2307	2311	2316	2344	2348	2351	2353
		9	2319	2318	2323	2327	2339	2345	2349	2351
			14	21	28	35	14	21	28	35
Club 5	RA_INJ	3	1979	1998	2002	2003	1981	2001	2000	2003
		5	1981	2002	2008	2010	1983	2003	2006	2009
		7	1986	2005	2010	2012	1986	2006	2009	2011
		9	1990	2008	2011	2013	1986	2006	2009	2011
	EWMA_INJ	3	1989	1992	1994	1995	1998	1994	1990	1989
		5	1990	1995	1998	1999	2002	1999	1996	1995
		7	1989	1997	2000	2002	2003	2001	1998	1997
		9	1990	1998	2002	2003	2003	2002	1999	1999
			14	21	28	35	14	21	28	35
Club 6	RA_INJ	3	1597	1608	1627	1628	1612	1624	1636	1638
		5	1594	1604	1629	1629	1602	1613	1627	1628
		7	1595	1611	1637	1630	1606	1618	1634	1630
		9	1591	1612	1637	1633	1609	1622	1640	1639
	EWMA_INJ	3	1595	1596	1598	1599	1625	1633	1640	1644
		5	1616	1614	1615	1617	1632	1638	1641	1643
		7	1631	1626	1626	1627	1631	1638	1640	1641
		9	1639	1634	1632	1632	1631	1637	1639	1640
			14	21	28	35	14	21	28	35
Club 7	RA_INJ	3	547	540	538	536	550	560	559	559
		5	563	561	562	563	563	565	565	565
		7	560	560	562	562	562	564	564	564
		9	561	561	561	560	563	564	564	565
	EWMA_INJ	3	536	532	529	528	560	550	545	542
		5	547	542	539	538	565	561	557	554
		7	556	550	547	546	565	563	560	558
		9	560	555	552	551	565	564	562	560

			Coupled				Uncoupled			
			14	21	28	35	14	21	28	35
Club 8	RA_INJ	3	1127	1129	1133	1135	1129	1132	1130	1132
		5	1127	1125	1128	1128	1124	1123	1126	1127
		7	1127	1124	1128	1131	1123	1120	1124	1127
		9	1129	1128	1128	1129	1125	1124	1123	1124
	EWMA_INJ	3	1126	1128	1129	1130	1153	1152	1148	1147
		5	1122	1122	1123	1124	1152	1150	1144	1141
		7	1121	1120	1121	1122	1152	1150	1142	1138
		9	1121	1120	1121	1122	1151	1149	1141	1137
			14	21	28	35	14	21	28	35
Club 9	RA_INJ	3	1029	1033	1022	1023	1035	1021	1016	1047
		5	1045	1043	1041	1042	1040	1039	1038	1044
		7	1046	1045	1045	1046	1041	1041	1043	1046
		9	1046	1049	1049	1051	1036	1041	1044	1049
	EWMA_INJ	3	1007	1006	1005	1004	1021	1033	1045	1050
		5	1012	1011	1011	1011	1031	1037	1047	1050
		7	1021	1021	1022	1022	1039	1042	1048	1050
		9	1028	1029	1029	1030	1043	1045	1049	1049
			14	21	28	35	14	21	28	35
Club 10	RA_INJ	3	581	578	581	584	583	584	584	585
		5	581	584	584	584	581	581	582	584
		7	581	586	586	586	584	585	586	586
		9	581	585	586	586	585	585	586	586
	EWMA_INJ	3	536	536	537	537	562	560	562	565
		5	552	553	555	556	573	572	573	573
		7	560	562	564	566	574	574	574	574
		9	565	567	569	571	574	574	574	574
			14	21	28	35	14	21	28	35
Club 11	RA_INJ	3	1677	1683	1695	1697	1683	1695	1697	1698
		5	1682	1681	1692	1692	1681	1691	1694	1696
		7	1685	1686	1697	1697	1684	1695	1696	1698
		9	1675	1686	1698	1699	1685	1697	1698	1699
	EWMA_INJ	3	1666	1671	1676	1680	1699	1700	1700	1699
		5	1681	1687	1692	1694	1691	1696	1698	1699
		7	1691	1695	1697	1699	1683	1690	1694	1696
		9	1695	1697	1699	1699	1677	1686	1690	1693
			14	21	28	35	14	21	28	35
Club 12	RA_INJ	3	1442	1448	1451	1453	1451	1457	1459	1461
		5	1455	1458	1459	1460	1457	1458	1460	1461
		7	1451	1458	1460	1461	1455	1459	1460	1461
		9	1450	1458	1461	1461	1455	1459	1460	1461
	EWMA_INJ	3	1444	1452	1454	1454	1444	1447	1449	1450
		5	1447	1456	1459	1460	1448	1451	1451	1452
		7	1449	1457	1460	1462	1448	1451	1451	1451
		9	1450	1457	1460	1462	1447	1450	1450	1450
			14	21	28	35	14	21	28	35
Club 13	RA_INJ	3	2329	2335	2343	2341	2322	2326	2330	2343
		5	2315	2321	2329	2330	2315	2320	2327	2340
		7	2319	2325	2333	2337	2320	2326	2331	2343
		9	2325	2330	2338	2341	2322	2328	2332	2344
	EWMA_INJ	3	2297	2317	2325	2328	2335	2335	2335	2335
		5	2287	2305	2314	2318	2334	2334	2334	2334
		7	2291	2305	2313	2317	2332	2333	2333	2333
		9	2296	2307	2314	2318	2332	2332	2332	2332
			14	21	28	35	14	21	28	35
All clubs	RA_INJ	3	20471	20560	20652	20701	20523	20611	20662	20711
		5	20524	20580	20644	20688	20561	20643	20690	20729
		7	20534	20610	20675	20714	20560	20643	20690	20730
		9	20513	20605	20667	20704	20554	20641	20689	20730
	EWMA_INJ	3	20307	20407	20470	20503	20724	20713	20711	20710
		5	20366	20444	20501	20534	20720	20719	20722	20724
		7	20463	20505	20547	20573	20717	20708	20715	20720
		9	20547	20554	20580	20598	20715	20701	20710	20717

Figure 5.1: Heatmaps demonstrating the AIC values of each different possible training load calculation method, including rolling averages, exponentially weighted averages, coupled and uncoupled data and 4 different acute (3,5,7 and 9 days) and chronic (14, 21, 28 and 35 days) time periods. Green cells represent lower values and are, therefore, more favourable than those in yellow, orange or red.

For each of the potential methods of acute:chronic workload ratio calculation, (i.e. coupled vs uncoupled, rolling vs EWM average and different acute and chronic time periods) an assessment was undertaken to establish the lowest possible AIC value and each of those different calculation methods to identify the most appropriate means of calculation (Figure 5.2 A, B, C, D, E, F). In these figures, if a measure was demonstrated by a club as first choice it was represented in the left-most column, while a measure with essentially no support was shown in the right-most column. Therefore ideally, the best supported calculation methods would display no clubs to the far-right of each graph, with a higher proportion to the left. Coupled load values represented the lowest AIC value in all 13 of the clubs (Figure 5.2A) whilst uncoupled loads were seen to have essentially no support in nine clubs, with four clubs displaying some degree of support for their use (Figure 5.2B). Rolling averages represented the lowest AIC value in five clubs, with a further two clubs demonstrating some support (Figure 5.2C). Despite this, 5 further clubs showed no empirical support for the use of rolling averages. In contrast, exponentially weighted averages were the best model fit in eight clubs, with three further clubs showing some support and two with essentially no support (Figure 5.2D). The two most common acute and chronic time periods used by clubs as the first choice model were 3-days and 14-days respectively (Table 5.1). Three-day acute load was the first choice model in nine clubs, with the remaining four clubs demonstrating at least some support for its use, with all AIC value differences <10 (Figure 5.2E). Fourteen-day chronic loads were the first choice model fit in nine clubs and also demonstrated support for their use in the remaining clubs, with values of <10 (Figure 5.2F).

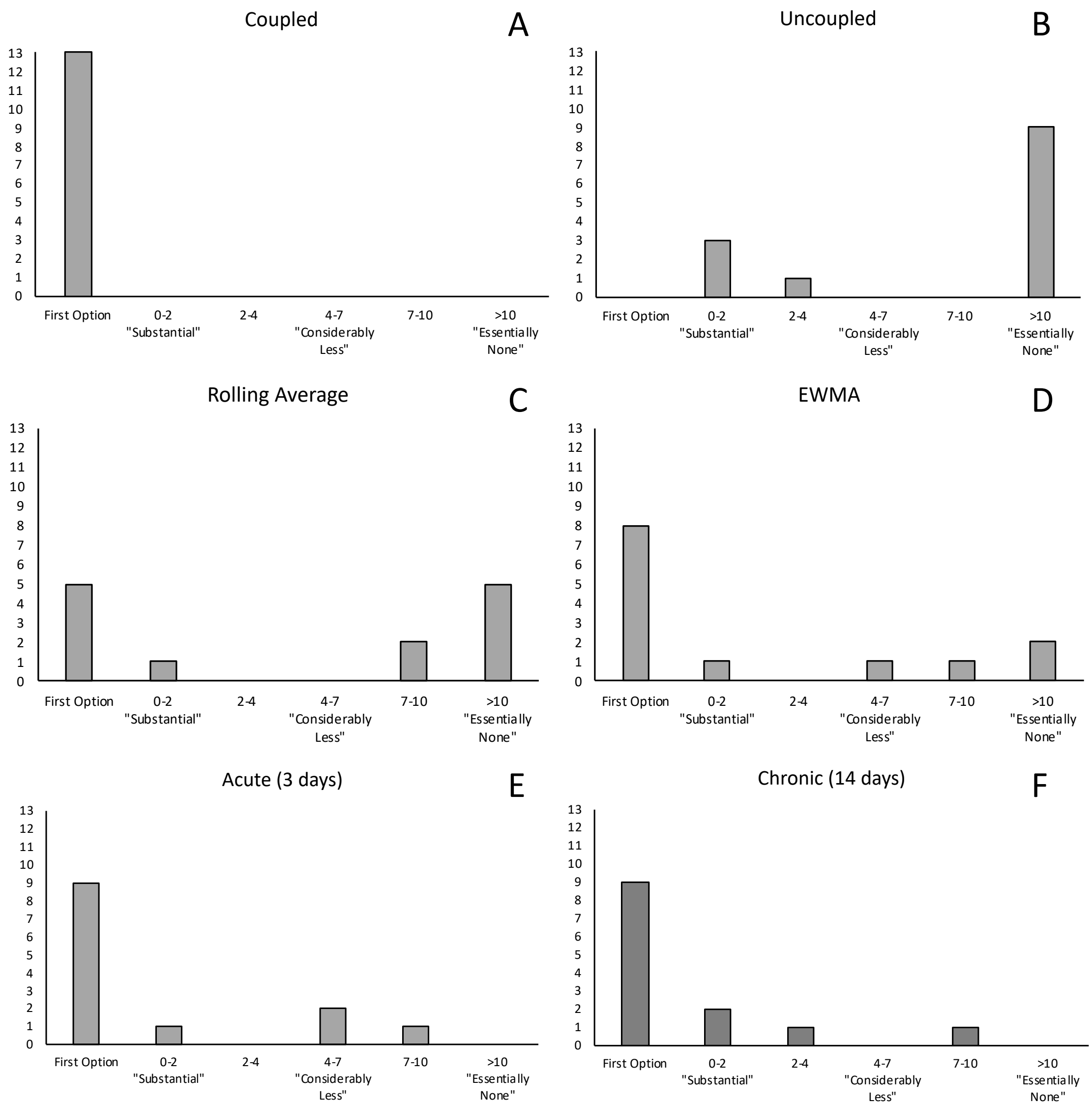

Figure 5.2: Comparisons between calculation methods for the acute:chronic workload ratio including coupled vs uncoupled (Part A and B), rolling vs exponentially weighted averages (Part C and D) and the most commonly used acute and chronic time periods, 3 and 14 days (Part E and F). The Y-axis represents the count of clubs in each category, with a more favourable model fit being on the left side of the X-axis and a model type with no empirical support being on the right side of the x-axis.

Assessment of the most commonly used acute:chronic workload ratio (7:28 day coupled loads) was undertaken for both rolling and exponentially weighted averages with the use of these time periods supported in only one club across the 13 (Figure 5.3A,B). The same time periods were used to examine the uncoupled equivalent values, again demonstrating very little support for its use (Figure 5.3C,D). Given the widespread variation in first choice calculation methods displayed by clubs, the coupled EWMA 3 to 14 day models were examined to investigate the support for its use in each club, having been selected as the first choice model when all data were analysed simultaneously (Table 5.1). The exponentially weighted 3 to 14 day coupled load was the first choice in three clubs, with further support for its use in eight clubs, with two clubs not demonstrating any support for the model (Figure 5.3F). Similarly, a rolling average derived 3 to 14 day acute:chronic ratio was selected as first choice in 3 clubs and was, therefore, investigated. This demonstrated that despite its selection by three clubs, and further support from a further three clubs, there were seven clubs that demonstrated no support for the use of this method (Figure 5.3E).

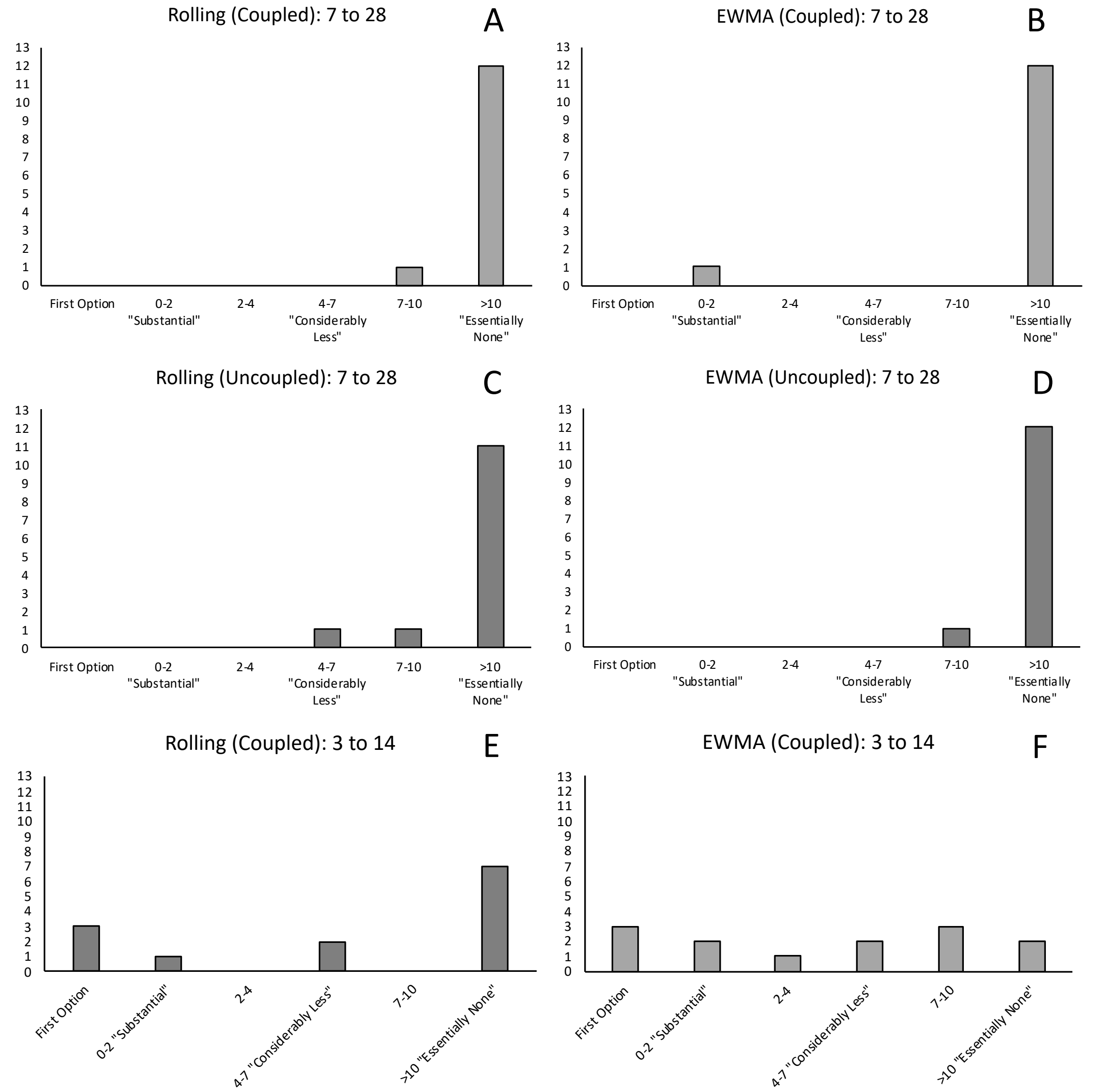

Figure 5.3: Comparisons between selected calculation methods for the acute:chronic workload ratio including Coupled 7: 28 day rolling and exponentially weighted averages (Part A and B), Uncoupled 7: 28 day rolling and exponentially weighted averages (Part C and D) and the acute:chronic ratio with the most support across all clubs (Part E and F). The Y-axis represents the count of clubs in each category, with a more favourable model fit being on the left side of the X-axis and a model type with no empirical support being on the right side of the x-axis.

When examining the most prudent time periods, coupling and averaging methods, both club-to-club (Figure 5.1) and season-to-season variation was apparent (Figure 5.4). Figure 5.4 shows EWMA (Coupled) 3 to 14 day ratios as the best fitting model during the 2015-16 season when all club's data were combined, yet in the 2016-17 season the rolling average equivalent demonstrated the best model fit. A similar analysis was undertaken using the AUC value to select the best performing model, with EWMA (Coupled) loads performing best in both 2015-16 and 2016-17 seasons (Appendix E).

			Coupled				Uncoupled			
			14	21	28	35	14	21	28	35
2015-16	RA_INJ	3	7113	7157	7179	7185	7119	7154	7174	7193
		5	7135	7167	7186	7192	7138	7165	7183	7198
		7	7134	7172	7191	7196	7136	7165	7183	7198
		9	7119	7169	7191	7194	7130	7163	7182	7197
	EWMA_INJ	3	7100	7143	7161	7166	7196	7161	7143	7140
		5	7108	7142	7159	7166	7210	7199	7184	7180
		7	7127	7149	7163	7168	7208	7205	7196	7193
		9	7143	7155	7165	7170	7205	7205	7198	7197
2016-17			14	21	28	35	14	21	28	35
	RA_INJ	3	13240	13305	13339	13391	13314	13386	13432	13467
		5	13345	13407	13430	13473	13378	13445	13483	13509
		7	13353	13410	13418	13458	13369	13434	13474	13503
		9	13381	13417	13420	13455	13366	13429	13468	13500
	EWMA_INJ	3	13423	13432	13438	13440	13486	13397	13400	13412
		5	13412	13411	13413	13413	13507	13423	13397	13409
		7	13420	13412	13409	13408	13515	13456	13413	13422
		9	13429	13417	13412	13409	13518	13479	13429	13435

Figure 5.4: AIC values for each season within the study, with all club's data combined.

5.4 Discussion:

The acute:chronic workload ratio is a popular training load measure used in multiple sports. However, the methods behind its calculation have been challenged in recent years, with a number of alternative approaches proposed, including coupled vs uncoupled values (Lolli et al., 2017), rolling vs exponentially weighted averages (Menaspa, 2017; Williams et al., 2016b; Murray et al., 2017a) and differing acute and chronic time periods (Carey et al., 2017a; Stares et al., 2018). This study aimed to examine an array of potential methodologies to establish the best fitting model for the use of sRPE data in a professional rugby union setting for injury risk management. It is clear from this investigation that there is substantial variation between clubs when selecting a model of best fit and that a 'one-size-fits-all' approach may not be appropriate. This investigation found that coupled, exponentially weighted averages over 3-day acute and 14-day chronic periods represented the best model fit on average, with support for its use in eleven out of the thirteen clubs, while the traditionally used 7 to 28 day RA model was supported in only one of thirteen possible clubs. Although widespread variation was evident, there was clear support for some calculation methods over others, with coupled providing a better fit than uncoupled, EWMA better than rolling averages and three and fourteen day acute and chronic periods providing a good model fit in the majority of clubs.

Despite eight unique combinations being identified as the first-choice combination of calculation methods across the 13 clubs (Table 1), there were two methods that demonstrated repeated selection as the first choice model (three clubs each); a rolling 3 to 14 day ratio as well as an exponentially weighted 3 to 14 day ratio (both coupled). Investigation of both of these methods led to the conclusion that the exponentially weighted average was supported in 11 of 13 clubs vs 6 of 13 using the rolling averages (Figure 5.3). This is not the first study to highlight the potential relevance of shorter than previously suggested acute and chronic periods in the management of injury risk, with Carey et al. (2017a) reporting the overall best time constants as being 3 and 21 days in Australian Footballers. Despite this, Carey et al. (2017a) also outlined how the most appropriate time constants were dependent on the session type and variable used, with 6:14 day loads for total distance explaining the most variation in injury likelihood when match and training was combined, while 3:21 day ratios using the moderate speed running variable explained the most variation in injury likelihood in matches alone (with moderate speed running used above other variables as it was the most commonly occurring top 3 workload parameter). In general, Carey et al. (2017a) reported that 3 and 6-day acute periods and 21 and 28-day chronic periods generated the best performing injury risk models, with the performance of the model showing higher sensitivity to the selection of acute time periods than chronic.

In the present study, the most commonly appearing best acute time window was 3 days, which was the best available option in nine cases, with some support in the remaining four clubs. This finding matches that of Carey et al. (2017a) and similarly in the context of rugby union, would for most clubs represent a period that includes the main training session prior to a match, but never the previous match itself. With regard to the chosen chronic period, 14-day loads were chosen as the best fit for the acute:chronic ratio in nine clubs, with the remaining four clubs showing some support for its use. Whilst this value is only half of the traditionally used 28-day period and 7 days less than the 21 day optimal period reported by Carey et al. (2017a), it represents a time frame over which fitness may decay should training cessation occur (Joo, 2018; Rodriguez-Fernandez et al., 2018). These findings, which used AIC to select the best model fit, were supported and validated with the use of AUC values, which showed the highest values for 3:14 day (coupled) exponentially weighted averages in 10 of the 13 clubs with values ranging from 0.69 to 0.72 (for those with 3:14 being the best model) and 0.63-0.70 (for those with other available best models; Appendix E).

In the majority of current training load literature, the most commonly used calculation method is the 7:28 day average value, which in this study was found to have little support for its use, with the majority of clubs showing no support for its use (Figure 5.3 A-D). This was supported further by the AUC measure with values of 0.50-0.67 using coupled data and 0.51-0.62 using uncoupled data (Appendix E). The lack of support for the 7 to 28 day method mirrors the findings of Carey et al. (2017a) , reporting R^2 values of between 0.04 to 0.41 in an Australian Football (AFL) population; however, in another AFL population, no differences were seen between the 7 to 28 day measures and other combinations (Stares et al., 2018). These findings suggest that the widely used 7:28 day value may not be appropriate in all settings, with a 3:14 day average the best fit in the context of sRPE derived load measures in rugby union. It is, therefore, advised that critique is applied prior to the use of any time windows in the context of the sport being played to identify the training or match demands involved in any given time window and whether they are representative of an athletes fitness or fatigue status.

Despite no single measure gaining the support of all 13 clubs, it was evident that exponentially weighted averages and coupled loads were superior in the majority of cases. Although there have the more common use of rolling averages, there has been previous support for a higher sensitivity of exponentially weighted averages for detecting changes in injury risk (Murray et al., 2017a; Esmaeili et al., 2018). These findings were supported in the current study, with more clubs showing support for the exponentially weighted averages (no support in 2 clubs: Figure 5.2D) than that of rolling averages (no support in 5 clubs: Figure 5.2C). This was validated using the AUC measure, with EWMA values outperforming rolling averages in all 13 clubs (Appendix E). While these results have been documented previously, this is the first study in rugby union to highlight the potential importance of exponentially weighted averages in training load calculations but also the first to demonstrate in a large cohort of multiple teams across a whole league the support for this calculation type.

This study is also the first to explore both coupled and uncoupled measures to assess the impact of mathematical coupling on injury risk management. When comparing the two methods, coupled values were the first choice method in all 13 clubs (Figure 5.2A), while uncoupled values were only supported in four of the 13 clubs (Figure 5.2B), with the uncoupled values demonstrating the highest AUC values in only one club (Appendix E). Despite the potential for spurious correlation within coupled datasets being documented elsewhere (Lolli et al., 2017), the present investigation shows little support for the uncoupled alternative.

When assessing the data as a grouped sample, the coupled and exponentially weighted average of 3 to 14 days produced the lowest AIC values (Figure 5.1). When split by season however, it was apparent that the best calculation was different in each season, with an exponential 3 to 14 day (coupled) load being the best fit in season one and the rolling average equivalent being the best fit in season two. This finding demonstrates that not only is there between setting (club) variation that exists, but also that this may be a dynamic process which should be part of an annual review of data processing strategies. With the substantial rise in data availability for player management in recent seasons, methods such as principle component analysis have been suggested to streamline the volume of variables being monitored by clubs while still capturing the distinct components of training load (Williams et al., 2017a). With such processes being undertaken to streamline the variables being collected, an assessment of the methods used to aggregate and calculate training load variables may also offer value to clubs. Based on the between-club and between-season differences demonstrated within this paper, such a process of assessing calculation methods is recommended in annual reviews of data capture systems to ensure the methods of player management are optimal. While this study is unique in its assessment of all the potential calculation methods in training load management, it also provides the large scale study called for by Quarrie et al. (2016).

Using this dataset going forward to outline the relationship between the optimal training load measures and injury risk in rugby union will utilise the strength of the large sample size by using a combined dataset, while the purpose of a club by club analysis in the context of this study is to demonstrate the problems associated with the adoption of a one-size fits all approach. Unlike the single-team studies of much research in this field, the league wide data capture allows us to see between club variation, which is likely to be substantial given the presence of 13 unique systems of play, methods of training and philosophies on athlete management. While this investigation has focused exclusively on rugby union, it is evident that other sports are likely to demonstrate similar patterns of variation with regard to modelling training load and injury risk, with the work of both Carey et al. (2017a) and Stares et al. (2018) outlining different optimal time windows in Australian football. Although training load and injury risk studies have been conducted across a wide range of sports, studies such as the present one outlining team-to-team variation for optimal analysis methods have not been undertaken and would offer similar utility in establishing the usefulness of a one size fits all approach to training load management.

This study is the largest of its type and the first to assess the implications of multiple combined training load variable calculation methods on model fit for athlete management. Despite this there are a number of limitations, including the use of a single internal load measure, not accounting for other moderators of injury risk and not including a latent period. The sRPE method is an internal training load measure and is just one of a substantial number of available training load tools used in elite sport (Halson, 2014). In this study this measure was used as it has previously been shown as widely used in rugby union (Comyns and Flanagan, 2013; Comyns and Hannon, 2018), can be used in multiple settings at once using the same methodology, has been validated across multiple other metrics of load (Coutts, 2009; Haddad et al., 2017) and can be applied to a host of modalities including aerobic training (Foster et al., 2001), strength training (Day et al., 2004) and other collision based field sports (Clarke et al., 2013). This measure accounts for the internal response of an athlete to training load and was used for this study as, given the size of the sample, the use of an external metric such as GPS would not have been feasible given the widespread variation in systems and definitions used by clubs. Further to this, in a recent review Eckard et al. (2018) reported that the link between training load and injury risk was strongest in measures of subjective internal load such as sRPE. Moreover, Quarrie et al. (2016) recommended the incorporation of sRPE into any measurement of load at the professional level within rugby union.

A second limitation associated with this study is the examination of training load metrics in isolation of potential confounders. Injury is a multifactorial and dynamic process (Meeuwisse et al., 2007) and as such, to attribute injury risk to one variable (training load) alone would be naïve. Examining training load in isolation in this study was done to isolate the independent fit of training data to injury risk models with the intention of applying the most appropriate methods in the context of wider injury risk in linked work (Part 2). The complexities involved with the analysis of this variable in isolation required the methodology to be clearly outlined prior to undertaking of a more comprehensive evaluation of the influence of training load on injury risk in combination with a number of moderating factors.

The final limitation associated with this study involves the lack of an injury lag period included in the analysis. Spikes in load have previously been reported to increase the risk of injury for up to 4 weeks (Orchard et al., 2009; Drew and Finch, 2016; Stares et al., 2018). It has, therefore, been suggested that a latent period be included in studies of this type to capture the role of temporality in the workload-injury relationship (Windt et al., 2018). In contrast to this evidence, Carey et al. (2017a) found no evidence for the inclusion of a lag period in injury risk analysis, whilst Esmaeili et al. (2018) did not include a lag period as the daily analysis used in that study allowed for any spike to be captured and accounted for in the chronic period, compared with previous studies that aggregated weekly values only: the same principle applies in the case of this study and, therefore, no lag period was included in the analysis.

In summary, this study is the first in rugby union to examine differing acute:chronic workload ratio calculation methods as well as the largest in any sport to assess the impact of these calculation methods on model fit for injury risk management. Despite widespread variation between clubs, the calculation method with the most support was for the use of a coupled and exponentially weighted average 3 to 14 day load, which was supported in all but 2 clubs. This contrasts with the most commonly used coupled rolling average of 7 to 28 days, which was supported in only one club. and the current study demonstrates the variation in 'optimal' methodological approaches across both teams and seasons. It is, therefore, recommended that an investigation such as this should become part of the continual improvement processes implemented within clubs to ensure the data is being maximised to its full potential. While this process has shown the widespread variation between optimal calculation methods between clubs and that a one size fits all approach may not suffice, the best fit method will be taken forward for further work investigating the relationship between training load and injury risk accounting for other potential confounders.

CHAPTER 6

Complexities of injuries risk management using training load data (Part 2): Associations between training load and injury

6.1 Introduction:

The application of training load monitoring practices across sports has grown in recent years, with this growth being driven by an increase in our understanding of training load as a modifiable injury risk factor (Drew and Finch, 2016; Jones et al., 2017; Eckard et al., 2018). Alongside the numerous individual studies investigating the training load-injury relationship, three systematic reviews have been conducted, synthesising this work and outlining the nature of the relationship across multiple sports (Drew and Finch, 2016; Jones et al., 2017; Eckard et al., 2018). Training load can be documented using multiple subjective and objective metrics that aim to capture either a player's external load (the work undertaken by an athlete) or internal load (the relative physiological or psychological stress imposed on the athlete as a result of the external load) (Impellizzeri et al., 2005; Halson, 2014). Having selected a method for capturing training load, one metric commonly used to manage individual player injury risk is the acute:chronic workload ratio, which historically is a measure of an athlete's training load in the last 7 days (acute) compared to the last 28 days (chronic) (Gabbett, 2016a). This metric has been shown to be associated with injury risk in multiple sports, including rugby league (Hulin et al., 2016a; Hulin et al., 2016b), soccer (Malone et al., 2017b; Bowen et al., 2017), Australian Football (Colby et al., 2017; Stares et al., 2018), and Gaelic Football (Malone et al., 2016). In rugby union, the use of the acute:chronic workload ratio to individually manage training load is less well established, with the only published study reporting an unclear association with injury risk (Cross et al., 2016b). Given some of the documented methodological issues associated with the calculation of the acute:chronic workload ratio (Williams et al., 2016b; Lolli et al., 2017; Lolli et al., 2018), a smoothed week-to-week load variable has also been suggested (Lazarus et al., 2017). This metric provides an alternative method of capturing spikes in load whilst overcoming the methodological issues associated with the use of ratios (Lazarus et al., 2017).

While the acute:chronic workload ratio has been widely adopted in practice as a method for managing injury risk to team sport athletes, a number of other workload related measures have been demonstrated to be important isolated risk factors and moderators of the acute:chronic workload and injury relationship. Both acute and chronic loads in isolation have been shown as risk factors for injury risk, with a rise in acute load associated with a rise in injury risk (Piggott et al., 2009; Rogalski et al., 2013; Hulin et al., 2014; Cross et al., 2016b), while moderate to high chronic loads have been shown to be associated with a reduction in injury risk (Cross et al., 2016b; Malone et al., 2017c; Stares et al., 2018). Further to these common measures, week-to-week changes in load have also demonstrated an association with injury risk in rugby union, with 2 standard deviation (SD) increases associated with a 60% increase in injury risk (Cross et al., 2016b). In addition to training related variables, it must be recognised that injury is multifactorial with several risk factors identified in previous literature (Meeuwisse et al., 2007). In rugby union these include previous injury (Williams et al., 2017c), previous concussion (Cross et al., 2015), match minutes in the preceding 12 months (Williams et al., 2017c), playing position (Brooks et al., 2005a) and player age (Brooks, 2004; Chalmers et al., 2012). While many of these factors are independently associated with injury risk, some may also moderate the influence of workload on injury outcomes. For example, in a recent study it was shown that the effect of chronic load on injury risk was underestimated by up to 20% until previous injury was included as a moderating risk factor within the injury risk models (Esmaeili et al., 2018). It is, therefore, important to determine whether previously identified risk factors moderate the injury-load relationship within rugby union (Windt et al., 2017).

In rugby union, the majority of injuries occur in contact, with 52% attributed to the tackle alone in match play (Kemp et al., 2019). Given this, when examining the relationship between load and injury risk in rugby union, it is important to capture whether the load of a player is associated with all types of injury, irrespective of mechanism. However, when considering the mechanisms by which training load may lead to injury, it is argued that errors in training load prescription are likely associated with overuse injuries (Drew and Purdam, 2016). While the higher proportion of injuries in rugby union occur in contact, a large number of non-contact soft tissue injuries are also apparent, particularly in training (Kemp et al., 2019). While the nature of contact injuries is often highly unpredictable, non-contact soft tissue injuries may, like all overuse type injuries, be the result of errors in training load prescription with the accumulation of fatigue causing a reduction in the stress bearing capacity of the tissue and, therefore, a reduction in the threshold for stress at which the tissues fail (Kumar, 2001). It is, therefore, the case that an analysis of non-contact soft tissue injuries alone be of practical use to the rugby union community, as these are more likely to be preventable than those associated with contact

Despite the proliferation of research articles investigating the relationship between training load and injury risk (with a recent methodological review reporting 34 studies using longitudinal data (Windt et al., 2018)), studies are typically small with a median of 46 athletes per study (Windt et al., 2018). The generalisability of these studies to other within-sport and between-sport settings may be limited by the innate differences in club philosophies and sports medicine structures between teams (Chapter Seven). The aim of this study was, therefore, to investigate the relationship between training load and injury risk in a large multi-club sample of professional rugby union players, and to investigate the moderating effects of established risk factors on this relationship.

6.2 Methods:

6.2.1 Participants

This study used an observational cohort design, capturing training load and injury data across a cohort of 13 elite rugby clubs competing in the top tier of English professional rugby union. Data was collected from 13 Premiership clubs over the 2015-16 and 2016-17 seasons (10 clubs for two seasons, three clubs for one season). Of a possible 668 and 707 registered players across the league, 433 and 569 players were recruited in the two seasons respectively, with 1002 total player-seasons included in the dataset (696 unique players). Injuries were collected through the Professional Rugby Injury Surveillance Project. Each player was provided with a participant information sheet and individual consent was obtained voluntarily. Players were included if both medical injury data and training load data were collected, with a minimum of 100 days of training data over a single season required for inclusion. The study was approved by the University of Bath Research Ethics Approval Committee for Health (Ref no. 15/16 252).

6.2.2 Procedures

Injury data was collected on site using an online capture platform (The Rugby Squad, The Sports Office UK Ltd.) with the assistance of medical staff (physiotherapists/doctors) using a 24 hour time-loss definition of "an injury that resulted in a player being unable to take a full part in future rugby training or match play for more than 24 h from midnight at the end of the day the injury was sustained" (Fuller et al., 2007c). Training load data was captured by club conditioning staff using the session Rating of Perceived Exertion (sRPE) method (Foster et al., 2001) given its suitability across multiple session types, ease in collection and consistent capture across all 13 clubs involved in the study. The measure involved the capture of a rating of global session intensity using a Borg CR-10 scale (Borg et al., 1987) within 30 minutes of the session completion, which was then multiplied by the session duration in minutes to provide a single sRPE value (in arbitrary unit (AU)) for the session (Foster et al., 2001). Further detail outlining the methods of data capture can be found in Chapter 3 of this PhD thesis. Alongside the training load metrics of interest, five well-documented injury risk factors were included in the dataset as covariates for each athlete including position, age, previous injury in the past 12 months, previous concussion in the past 12 months and match minutes in the past 12 months. Player position was obtained using individual player baseline data reported at the start of each season, recorded on the online medical platform (The Rugby Squad, The Sports Office UK Ltd.). The six categories used were divided into front row, second row and back row (forwards) and half backs, centres and the back three (backs). Further to this, age was recorded as part of the standard pre-season baseline data entry for each player. Previous injury and previous concussion were captured by the primary researcher by retrospectively analysing the previous seasons injury data to identify individual cases of previous injury/ concussion for each player. These were recorded as counts per player in an Excel spreadsheet and added to the database of all covariates and training load data. Match minutes were recorded using an online data capture platform ("Elitehub", RFU, 2019), as outlined in Chapter 3 and summed over a rolling 12 month period. The selection of reference categories has previously been reported as a challenge to analysing the training load-injury risk relationship, as the freedom in choice of the selected category can lead to changes in the reported findings (Carey et al., 2018). The selection of each reference category in this work was undertaken *a priori*. Both position and age reference categories were arbitrarily assigned as the "Back 3" positional grouping and the 18-23 year old age grouping, respectively. A "moderate-low" grouping of 1 previous injury was selected for previous injury as the data demonstrated that the majority of players were likely to experience one injury per 12 months (69% in 2015-16 and 77% in 2016-17). In contrast, the "Low" (no previous concussion in the past 12 months) previous concussion category was chosen as the reference as the majority of players did not experience one concussion over a rolling 12 month period (% of players experiencing at least one concussion: 23% in 15-16 and 28% in 16-17). A "moderate-low" category (455-888 minutes or 5.7-11.1 full match equivalents) for match minutes was chosen as it has previously been shown as a high risk in rugby union (Williams et al., 2017c).

To express injury on each day, a binary injury indicator (0-No/ Yes-1) was included for each athlete on each day of the study period. Only days on which a player was exposed to load were included in the analysis. Days on which a player exhibited no load were excluded from analysis because to include them would have added a significant number of "0" values to the analysis, despite no rugby-related injury being possible on that day. No latent period was included, as the derived measures were updated and analysed daily (Esmaeili et al., 2018).

6.2.3 Data Analysis

Following the assessment of different calculation methods, including coupled and uncoupled data, exponentially weighted and rolling averages, and differing acute and chronic time windows, the coupled and exponentially weighted moving average (EWMA) with time constants of 3 to 14 days was used as the acute:chronic workload ratio for analysis of the training injury relationship (Chapter 5). This data was exported alongside acute (3 day exponentially weighted average) and chronic (14 day exponentially weighted average) measures, while a new week-to-week change metric was calculated as a smoothed difference of week-to-week load scores as described by Lazarus et al. (2017) as differential load. This differential load represents a smoothed rate of change in load from one week to another (Lazarus et al., 2017). Independent univariate generalised linear mixed models for each covariate were used to identify their association with injury risk in this population. This was undertaken using the "glmer" function of the "lme4" package (Bates et al., 2018), with fixed effect terms as each covariate, random effects for each player nested within each individual team and a complimentary binomial loglog-link term. As per Williams et al. (2017c), magnitude based inferences (MBIs) were used to assess the importance of the model outcome, which are based on effect size and corresponding confidence intervals (CIs) in relation to a smallest worthwhile change with thresholds for benefit and harm set as hazard ratios of 0.90 and 1.11, respectively (Hopkins, 2010). Unclear effects were reported if 90% CIs crossed both the threshold for harm and benefit by 5% (Hopkins et al., 2009). Should the effect be clear, it can be termed as beneficial, harmful or trivial (less than the smallest worthwhile change), with the strength of the effect expressed using a qualitative probabilistic term using the following thresholds: <0.5%, most unlikely; 0.5-5%, very unlikely; 5-25%, unlikely; 25-75% possibly; 75-95%, likely; 95-99.5%, very likely; >99.5%, most likely (Hopkins et al., 2009). Univariate risk factors associated with at least a "*likely*" effect on injury risk were retained for inclusion in further analysis. Responses of covariates were assessed for non-linearity using quadratic terms within each univariate model (Williams et al., 2017c). Each covariate demonstrated a non-linear relationship with injury and were, therefore, split into categories for analysis.

All univariate risk factors (with at least a "*likely*" relationship with injury) and a fixed load measurement of interest (i.e. the acute:chronic workload ratio) were entered into a multivariate generalized linear mixed-effects model (Equation 6.1) . Using the "GLMERSelect" function of the "Statistical Models" package (Newbold, 2019), both interaction terms and main effects were assessed using a backwards stepwise selection of fixed effects, retaining only the most important covariates in the final model. The covariates retained by the backwards selection of fixed effects and three training load measures were included in the final models to investigate injury risk. Multicollinearity between covariates was assessed using Variance Inflation Factors (VIF), with a VIF of ≥10 deemed to show substantial collinearity (Kutner, Nachtsheim and Neter, 2004; Cross et al., 2016b). The three load measures included were an acute load (3 days), a chronic load (14 days) and either the acute:chronic workload ratio (3 to 14 day exponentially weighted and uncoupled) or a smoothed week-to-week change variable. These load measurements were used to represent an acute, chronic and change in load measure, previously outlined as important by principal component analysis of training load data in this setting (Williams et al., 2017a).

Equation 6.1

$$\gamma ij = \beta_0 + \beta_{1x1ij} + \beta_{2x2ij} + \ldots + u_j + e_{ij}$$

Final analysis of the training load and injury risk relationship was undertaken for two separate outcome measurements, all injury types and non-contact soft tissue injuries only. For the purpose of this analysis, soft tissue injuries were defined as any muscle tendon or ligament issue not occurring from a contact mechanism. The acute:chronic workload variable was divided into quintiles, with equal observations in each group; the five cut points were 0, 0.37, 0.82,1.26 and 3.76. Injury risk was expressed as the injury hazard (risk per player per exposure day, with comparisons between groups expressed as hazard ratios with 90% confidence intervals (Esmaeili et al., 2018). Confidence intervals were set at 90% to allow for the possibility that the true value lies 5% either below the lower limit or above the upper limit (Batterham and Hopkins, 2006). All analysis was undertaken using RStudio (RStudio, Inc. Version 1.1.463).

6.3 Results:

A total of 1718 time-loss injuries were sustained across the two-season period while over 130,000 sRPE TRIMP training load scores were captured from the 696 unique athletes across the 13 clubs involved in the study. Of these, 383 injuries were non-contact soft tissue injuries, which were analysed as a secondary analysis.

6.3.1 Univariate Analysis- All Injury

When examining all injury types, univariate analyses found age, previous injury, previous concussion and match minutes to have "*likely*" substantial effects on all injury risk, while position demonstrated "*possibly"* substantial effects with the majority of positions demonstrating unclear findings (Table 6.1). Players aged 18-23 had the lowest risk of injury with the 27-29 age group representing the highest risk, with a relative risk (RR) of 1.35 (90% CIs: 1.16-1.57). Analysis of previous injury found that the greater the number of previous injuries, the greater the risk of subsequent injury, with no previous injury being "*most likely beneficial*" to subsequent risk. A history of previous concussion within a 12-month period was associated with a "*likely harmful*" effect (RR: 2.39, 90%CIs: 2.17-2.63). There was a clear increase in risk associated with number of match minutes played in the preceding twelve months. Risk increased with each respective match minute category, with the highest category of 1402-2681 (18-34 full-match equivalents) minutes representing the highest risk (RR: 1.49, 90% CIs:1.31-1.71).

6.3.2 Univariate Analysis- Non-contact soft tissue Injury

When examining non-contact soft tissue injury only, univariate analysis found that previous injury and previous concussion represented at least "*likely*" effects on all injury risk, while age, position and match minutes demonstrated "*Possible*" and "*Unclear*" effects respectively (Table 6.2). The oldest age group (30-39 years old) demonstrated the highest risk of injury (RR: 1.22, 90% CIs: 0.95-1.57); however, this was only "*Possibly Harmful*". Similarly to all injury types, the highest category of previous injuries represented the highest risk (RR: 2.05, 90% CIs:1.66-2.53), while having a previous concussion in the past 12 months was also associated with an increased risk of injury (RR: 1.46, 90% CIs:1.21-1.77). Only possible associations between match minutes and non-contact soft tissue injury risk were demonstrated, with "Mod High" (889-1401 or 11.1 to 17.5 match equivalents) representing the lowest risk.

Table 6.1: Univariate analysis of each covariate analysed as risk factors for injury risk independently (All injuries included). Effects with at least *"likely"* magnitude based inference (MBI) values retained for multivariate models. Likelihood of increased risk of injuries: * possibly, ** likely, ***very likely, ****most likely

Variable	Category	Unit	Relative Risk (90%	*P*-Value
Position	Back 3 (Ref)	Back 3 (Ref)	1.0	
	Centres	Centres	1.07 (0.86-1.34)	0.60
	Half Backs	Half Backs	0.88 (0.71-1.09)*	0.33
	Back Row	Back Row	1.06 (0.86-1.30)	0.65
	Second Row	Second Row	1.0 (0.80-1.24)	0.99
	Front Row	Front Row	0.94 (0.77-1.14)	0.59
Age	Low	18-23	1.0	
	Mod Low	24-26	1.29 (1.12-1.48)***	<0.01
	Mod High	27-29	1.35 (1.16-1.57)***	<0.01
	High	30-39	1.26 (1.08-1.47)***	0.01
Previous Injury	Low	0	0.03 (0.02-0.04)****	<0.01
	Mod Low	1	1.0	
	Mod High	2	1.51 (1.35-1.69)***	<0.01
	High	3-12	2.5 (2.25-2.73)****	<0.01
Previous Concussion	No	No	1.0	
	Yes	Yes	2.39 (2.17-2.63)****	<0.01
Match Minutes	Low	0-454	0.79 (0.68-0.90)***	<0.01
	Mod Low	455-888	1.0	
	Mod High	889-1401	1.15 (1.02-1.31)*	0.06
	High	1402-2681	1.49 (1.31-1.71)***	<0.01

6.3.3 Backwards stepwise selection of model fixed effects

All univariate variables representing at least *"likely"* effects on injury risk were entered into a backward stepwise selection process to identify important fixed effects for further modelling. Variables with clear effects in either the all injury or non-contact soft tissue injury analysis were included in the backwards stepwise elimination process to ensure comparison across groups, i.e. player age, previous injury, previous concussion and match minutes played. This process concluded that in the case of both the all injury and non-contact soft tissue injury analysis, previous injury, previous concussion and match minutes should be retained in the final model, while age should not be included.

Table 6.2: Univariate analysis of each covariate analysed as risk factors for injury risk independently (Non-contact soft tissue injuries only). Effects with at least *"likely"* magnitude based inference (MBI) values retained for multivariate models. Likelihood of increased risk of injuries: * possibly, ** likely, ***very likely, ****most likely

Variable	Category	Unit	Relative Risk (90%	P-Value
Position	Back 3 (Ref)	Back 3 (Ref)	1.0	
	Centres	Centres	1.11 (0.78-1.58)	0.63
	Half Backs	Half Backs	0.99 (0.71-1.39)	0.97
	Back Row	Back Row	0.91 (0.65-1.27)	0.63
	Second Row	Second Row	1.19 (0.85-1.67)	0.40
	Front Row	Front Row	0.92 (0.67-1.25)	0.65
Age	Low	18-23	1.0	
	Mod Low	24-26	1.11 (0.87-1.42)	0.49
	Mod High	27-29	1.20 (0.93-1.55)*	0.25
	High	30-39	1.22 (0.95-1.57)*	0.20
Previous Injury	Low	0	0.09 (0.06-0.15)****	<0.01
	Mod Low	1	1.0	
	Mod High	2	1.38 (1.09-1.75)**	0.02
	High	3-12	2.05 (1.66-2.53)****	<0.01
Previous Concussion	No	No	1.0	
	Yes	Yes	1.46 (1.21-1.77)***	<0.01
Match Minutes	Low	0-454	0.92 (0.72-1.17)	0.57
	Mod Low	455-888	1.0	
	Mod High	889-1401	0.82 (0.64-1.05)*	0.18
	High	1402-2681	1.02 (0.80-1.31)	0.87

6.3.4 Final model selection

Despite both the acute:chronic workload ratio and a smoothed differential load value being examined, the differential load variable displayed mostly "*Unclear*" findings and, therefore, the focus of this section will be on the acute:chronic workload variable (Differential load tables can be seen in Appendix F). The final models were composed of the following elements:

- Injury measure
  - All Injury
  - Non-contact soft tissue Injury
- Fixed effects
  - Acute:chronic workload ratio (EWMA 3 to 14 day)
  - Acute:chronic workload ratio (EWMA 3 to 14 day)^2 (to account for non-linearity of the load-injury relationship)
  - Acute load (3 day)
  - Chronic load (14 day)
  - Previous injury in the preceding 12 months
  - Previous concussion in the preceding 12 months
  - Match minutes in the preceding 12 months

- Random effects
    - Player nested within team

6.3.5 Acute:chronic workload ratio and all injury

After adjusting for other risk factors, the relationship between previous injury, previous concussion and match minutes in the preceding 12 month period varied from that of the univariate models alone (Table 6.3). The effect of previous injury was reduced when adjusted for other risk factors while a similar finding was apparent in previous concussion, with the relative risk associated with having a previous concussion dropping substantially after the inclusion of other covariates (2.39-unadjusted to 1.12- adjusted). Most notably, the association between match minutes and injury risk shifted to demonstrate playing a low number of match minutes (0-454) was higher risk than playing more match minutes. When unadjusted, playing between 889-1401 and 1402-2681 match minutes exhibited the highest risk; however, after adjusting for other risk factors, these categories demonstrated only "*possibly trivial*" and *"likely trivial"* changes. Examining acute loads in isolation, the higher the acute load, the greater the risk of injury, with acute load values of 378-2002 AU associated with a *"likely"* harmful effect on injury risk (RR:1.39, 90% CIs 1.10-1.76). Moderate high chronic loads (248-337 AU) were associated with the highest risk of injury with a "*very likely*" harmful effect evident (RR:1.30, 90% CIs 1.15-1.47).

Examining the relationship between the acute:chronic workload ratio as a risk factor, adjusted for other covariates, demonstrated a U-shaped relationship with injury risk (Figure 6.1). The resultant model was associated with an area under the curve (AUC) value of 0.76. Injury risk was highest on days with a low acute:chronic value (Injury Hazard 2.1%, 90% CIs: 1.6-2.6%), with this low value (acute:chronic of close to 0) associated with a "*most likely*" harmful hazard ratio of 1.9 (90% CIs 1.4-2.6) compared to the median reference value of 0.82 (Table 6.4). The quintile value representing the lowest risk was an acute:chronic of 1.26, which was associated with an injury hazard of 0.8% (90% CIs: 0.7-1.0%) and demonstrated a *"likely"* beneficial hazard ratio of 0.7 (90% CIs 0.6-0.9) versus the reference.

Table 6.3: Effect of previously identified risk factors after inclusion in multivariate model. Likelihood of substantially modified risk of injury: * possibly, ** likely, ***very likely, ****most likely. Outcome measure: All injury

Variable	Category	Unit	Relative Risk (90% CIs)-unadjusted	New Relative Risk (adjusted for other covariates)	Change in relative risk after adjustment
Previous Injury	Low	0	0.03 (0.02-0.04)	0.02 (0.02-0.04) ****	1% ↓
	Mod Low	1	1.0	1.0	
	Mod High	2	1.51 (1.35-1.69)	1.48 (1.32-1.66)****	3% ↓
	High	3-12	2.5 (2.25-2.73)	2.39 (2.15-2.66)****	11% ↓
Previous Concussion	No	No	1.0	1.0	
	Yes	Yes	2.39 (2.17-2.63)	1.12 (1.03-1.22)*	127% ↓
Match Minutes	Low	0-454	0.79 (0.68-0.90)	1.34 (1.18-1.53)***	55% ↑
	Mod Low	455-888	1.0	1.0	
	Mod High	889-1401	1.15 (1.02-1.31)	0.92 (0.82-1.03)*	23% ↓
	High	1402-2681	1.49 (1.31-1.71)	0.98 (0.87-1.10)**	51% ↓
Acute Load (AU)	Low	0-60	0.55(0.37-0.81)	0.37 (0.24-0.59)****	18% ↓
	Mod Low	61-205	1.0	1.0	
	Mod High	206-377	0.97 (0.86-1.09)	1.14 (0.97-1.34)*	17% ↑
	High	378-2002	0.88 (0.78-0.99)	1.39 (1.10-1.76)**	51% ↑
Chronic Load (AU)	Low	0-157	0.87 (0.74-1.03)	1.04 (0.87-1.27)	17% ↑
	Mod Low	158-247	1.0	1.0	
	Mod High	248-337	1.27 (1.14-1.41)	1.30 (1.15-1.47)***	3% ↑
	High	337-1560	0.90 (0.80-1.00)	1.07 (0.91-1.25)*	17% ↑

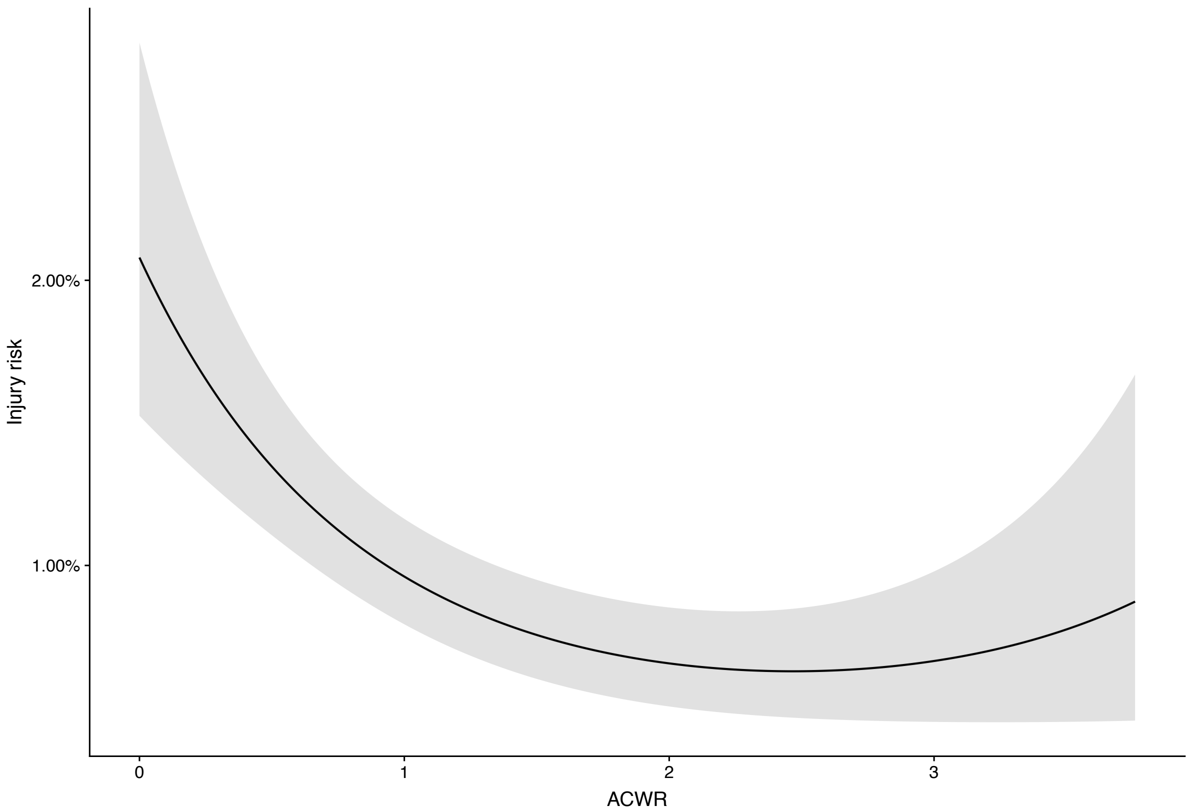

Figure 6.1: Effect of training load adjusted for acute load, chronic load, previous injury, previous concussion and 12 month exposure to match play. Y-axis: Injury Hazard: risk per player per exposure day. X-axis: ACWR (acute:chronic workload ratio). Outcome measure: All injury.

Table 6.4: Effect of training load adjusted for acute load, chronic load, previous injury, previous concussion and 12 month exposure to match play. Injury Hazard: risk per player per exposure day. Likelihood of change in risk of injuries: * possibly, ** likely, ***very likely, ****most likely. Outcome measure: All injury

Injury Measure	Training Load Variable	Quintile	ACWR Value	Injury Hazard % (90% CIs)	Hazard Ratio (90% CIs)
All Injury	ACWR	0	0	2.1 (1.6-2.6)	1.9 (1.4-2.6) ****
		0.25	0.37	1.5 (1.3-1.8)	1.4 (1.1-1.7)**
		Median	0.82	1.1 (0.9-1.3)	1.0
		0.75	1.26	0.8 (0.7-1.0)	0.7 (0.6-0.9)**
		1	3.76	0.9 (0.4-1.6)	0.8 (0.4-1.6)

6.3.6 Acute:chronic workload ratio and non-contact soft tissue injury

As with all injury, adjusting for the effect of multiple risk factors demonstrated changes in the relationship between previous injury, concussion and match minutes with non-contact soft tissue injury risk (Table 6.5). In contrast to all injury, when examining non-contact soft tissue injury the effect of previous injury was increased when accounting for other risk factors. In the case of previous concussion, adjusting for other covariates caused a reduction in the effect of having a previous concussion on subsequent injury risk. Interestingly, this adjustment meant that a history of concussion no longer had a harmful effect but that of a *"likely"* beneficial one. When adjusted for other covariates, the association between match minutes and non-contact soft tissue injury risk shifted, with players exposed to a low number of match minutes (0-454) being at higher risk than playing more match minutes. When unadjusted, playing between 889-1401 and 1402-2681 match minutes exhibited the highest risk; however, after adjusting for other risk factors, these categories demonstrated only "very likely" trivial and *"likely"* trivial changes. When examining acute loads in isolation, unlike the all injury analysis, there were no clear effects of acute load on injury risk. However, similar to that of all injury, moderate high chronic loads (248-337 AU) were associated with the highest risk of injury with a "*likely*" harmful effect evident (RR:1.40, 90% CIs 1.07-1.82).

Table 6.5: Effect of previously identified risk factors after inclusion in multivariate model. Likelihood of change in risk of injuries: * possibly, ** likely, ***very likely, ****most likely. Outcome measure: Non-contact soft tissue injury only

Variable	Category	Unit	Relative Risk (90% CIs)-unadjusted	New Relative Risk (adjusted for other covariates)	Change in relative risk after adjustment
Previous Injury	Low	0	0.09 (0.06-0.15)	0.07 (0.05-0.12)****	2% ↓
	Mod Low	1	1.0	1.0	
	Mod High	2	1.38 (1.09-1.75)	1.54 (1.21-1.96)***	16% ↑
	High	3-12	2.05 (1.66-2.53)	2.5 (2.0-3.11)****	45% ↑
Previous Concussion	No	No	1.0		
	Yes	Yes	1.46 (1.21-1.77)	0.76 (0.63-0.91)**	70% ↓
Match Minutes	Low	0-454	0.92 (0.72-1.17)	1.45 (1.13-1.86)***	53% ↑
	Mod Low	455-888	1.0		
	Mod High	889-1401	0.82 (0.64-1.05)	0.67 (0.53-0.86)***	15% ↓
	High	1402-2681	1.02 (0.80-1.31)	0.71 (0.56-0.91)**	31% ↓
Acute Load	Low	0-60	1.70 (0.73-3.99)	1.26 (0.50-3.13)	44% ↓
	Mod Low	61-205	1.0	1.0	
	Mod High	206-377	0.95 (0.73-1.24)	1.13 (0.80-1.60)	18% ↑
	High	378-2002	0.82(0.64-1.05)	1.25 (0.76-2.05)	43% ↑
Chronic Load	Low	0-157	1.01 (0.71-1.46)	1.01 (0.67-1.54)	0%
	Mod Low	158-247	1.0		
	Mod High	248-337	1.24 (0.99-1.56)	1.40 (1.07-1.82)**	16% ↑
	High	337-1560	0.92 (0.73-1.67)	1.26 (0.89-1.77)	34% ↑

The relationship between the acute:chronic workload and non-contact soft tissue injury was similar to that of all injury with the highest risk at both the low and high ends of the scale (Figure 6.2). Despite this, the injury hazard associated with non-contact soft tissue injury was lower than that of all injury. The resultant model was associated with an AUC value of 0.75. Injury risk was highest on days with a low acute:chronic value (Injury Hazard 0.7%, 90% CIs: 0.3-1.1) while this low value was associated with a "*very likely*" harmful hazard ratio of 2.3 (90%CIs: 1.1-4.9) compared to the median reference value of 0.82 (Table 6.6). The quintile value representing the lowest risk was an acute:chronic of 1.26, which was associated with an injury hazard of 0.2 (90% CIs: 0.2-0.4) and demonstrated a *"likely"* beneficial hazard ratio of 0.7 (90%CIs: 0.4-1.1). The acute:chronic value with the lowest risk was 2.15 with an injury hazard of 0.2 (90% CIs: 0.1-0.3); however, this acute:chronic value demonstrated an unclear effect on injury risk (HR: 0.7, 90%CIs: 0.3-1.3).

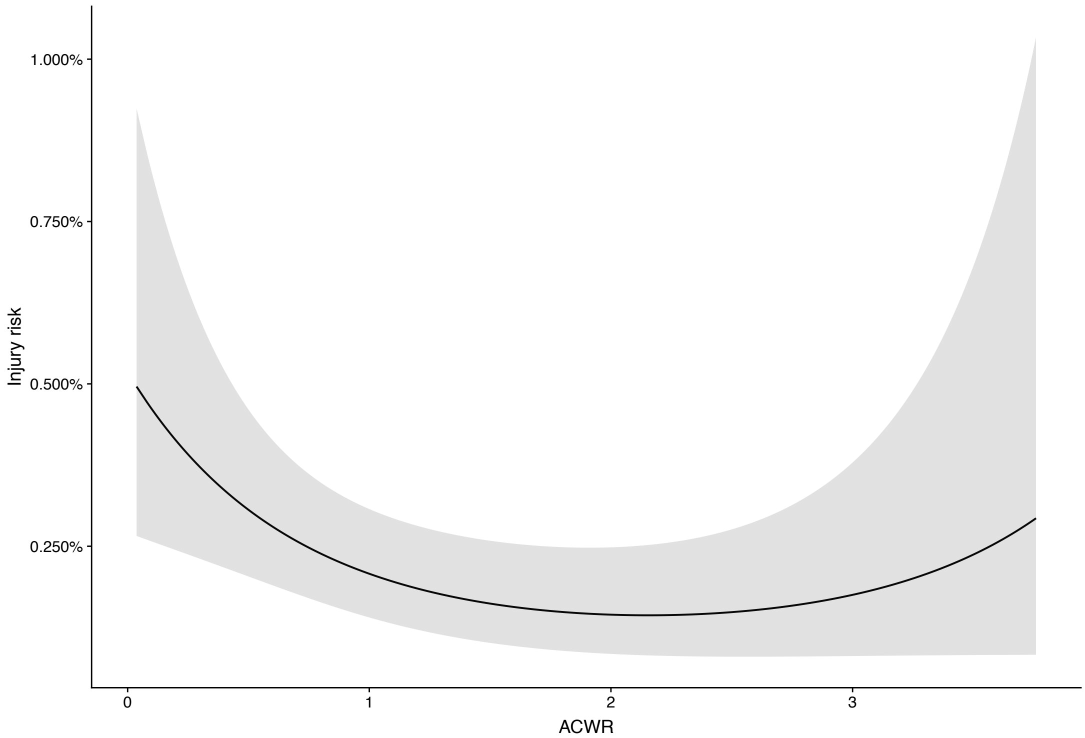

Figure 6.2: Effect of training load adjusted for acute load, chronic load, previous injury, previous concussion and 12 month exposure to match play. Y-axis: Injury Hazard: risk per player per exposure day. X-axis: ACWR (acute:chronic workload ratio). Outcome measure: Non-contact soft tissue injury only

Table 6.6: Effect of training load adjusted for acute load, chronic load, previous injury, previous concussion and 12 month exposure to match play. Injury Hazard: risk per player per exposure day. Likelihood of change in risk of injuries: * possibly, ** likely, ***very likely, ****most likely. Outcome measure: Non-contact soft tissue injury only.

Injury Measure	Training Load Variable	Quintile	ACWR Value	Injury Hazard % (90% CIs)	Hazard Ratio (90% CIs)
Non-contact soft tissue injuries	ACWR	0	0	0.7 (0.3-1.1)	2.3 (1.1 - 4.9) ***
		0.25	0.37	0.5 (0.3-0.6)	1.4 (1.0-2.7)**
		Median (Ref)	0.82	0.3 (0.2-0.4)	1.0
		0.75	1.26	0.2 (0.2-0.4)	0.7 (0.4-1.1)**
		1	3.76	0.4 (0.1-1.0)	1.3 (0.4-4.4)

6.4 Discussion:

This study represents the largest training load and injury study in any sport (Windt et al., 2018), with data collected over two seasons from 696 unique players, accounting for over 1000 player seasons within which over 1700 time loss injuries were reported. The relationship between training load was assessed for its association with all injury types and non-contact soft tissue injuries specifically. When examining all injury types, a "*most likely*" harmful effect on injury risk was seen when acute:chronic values were low (0-0.37) with a lower risk demonstrated when a players acute:chronic was near the 75th percentile (1.26), which demonstrated a "*likely beneficial*" effect on injury risk (Table 6.4). For non-contact soft tissue injuries, a similar finding was evident, with low values representing a "*most likely*" harmful effect on injury risk with, acute:chronic values near the 75th percentile value also representing a lower risk (Table 6.6). Comparing the results of univariate models to multivariate models of risk factors demonstrated substantial changes in outcomes based on the adjustment made for multiple covariates. Of the previously documented risk factors included, previous injury demonstrated the greatest impact upon subsequent risk of both all injury and non-contact soft tissue injury.

In the past decade, the evidence supporting training load as a modifiable risk factor for injury has grown dramatically with clear associations demonstrated across multiple sports. The acute:chronic workload ratio has been associated with injury risk in rugby league (Hulin et al., 2016a; Hulin et al., 2016b), soccer (Malone et al., 2017b; Bowen et al., 2017), Australian football (Colby et al., 2017; Stares et al., 2018) and Gaelic football (Malone et al., 2016) among others, with varying acute:chronic workload values being reported as favourable for minimising risk. In rugby union, the relationship between the acute:chronic workload ratio and injury risk has been investigated on one previous occasion, with an unclear relationship evident (Cross et al., 2016b). This study, therefore, is the first to show clear associations between the acute:chronic workload ratio and injury in rugby union, with clear associations for soft-tissue injuries alone, as well as all injuries. In this study, both in the case of all injury and non-contact soft tissue injury, a U-shaped curve was evident, with an elevated risk at both the lower and upper range of acute:chronic values; however, these changes were only seen to be clear at the lower end of the scale. Using all injury as the outcome measure, a low acute:chronic value represented a "*most likely*" harmful effect on injury risk. Using non-contact soft tissue as the outcome measure, a low acute:chronic value also represented the highest risk with a "*very likely*" harmful effect. While the evidence regarding the relationship between the acute:chronic workload ratio and injury has previously reported a sweet spot (Blanch and Gabbett, 2016; Gabbett, 2016a; Malone et al., 2017b; Weiss et al., 2017; Stares et al., 2018), there is evidence that spikes in load (as individually defined by each unique study: range >1.6 to >2.11) often represent the greatest increase in risk to athletes (Hulin et al., 2014; Hulin et al., 2016a; Hulin et al., 2016b; Murray et al., 2017b). Despite the findings of this study for all injury and non-contact soft tissue injury alone, mirroring one another, the absolute injury hazard of all injury was greater than that of non-contact soft tissue injury (2.1% vs 0.7% respectively). While a U-shaped curve was evident, the observations at the upper end of the range were few in number and, therefore, the confidence intervals are wide and the findings unclear. Compared to the median value of 0.82, an acute:chronic value of 1.26 represented a "likely beneficial" effect for minimising all injury and non-contact soft tissue injury risk and is similar to the range previously described as a sweet spot in other sports (Blanch and Gabbett, 2016; Gabbett, 2016a). Despite this value (1.26) falling between previously reported sweet spot values, it would appear that in this study, the acute:chronic workload value representing the lowest injury risk may fall at a higher range of values than that previously documented, for both non-contact soft tissue injuries only and all injury types. The reason for this may be due to the innate differences between historically calculated acute:chronic workload ratios (using 7 and 28 day acute and chronic periods), compared with those used in this study (3 and 14 day periods). These values were chosen as a result of the work undertaken in Chapter 5, providing objective evidence for the use of these timeframes when examining injury risk.

There are three plausible reasons why low acute:chronic workloads have the highest injury risk. Players falling in this category may have non-time loss injuries/pain, which may not omit them from team selection but warrant a lower managed load generally for a short period of time. The second possibility is that players require regular exposure to training stimulus. In the case of match injuries, this means that players are required to attain a training stimulus in the three days leading up a match. The structure of the 3 days prior to a game is likely to be week and team specific but will often include at least one training exposure. If a player was to be unavailable for these sessions, this would mean exposure to a first load in the acute 3-day period being that of match play would leave an athlete with a low acute:chronic workload and, therefore, a high risk of injury. The final plausible option is that the shorter time period over which the acute:chronic workload is being applied means an increase in the sensitivity of the measure to fluctuations in day-to-day changes in training and, therefore, the relevance of training within each weekly block becomes of greater relevance, with a more even spread across a 7 day block being more appropriate than that of a front-loaded training week. While this theory was not explored in the current analysis, an assessment of weekly structure in the days leading up to an injury in future work may allow for a greater understanding of whether this shorter 3-day acute period is in fact a determining factor in injury risk. Although it is not known whether the change in acute:chronic workload ratio calculation is responsible for the changes in the risk profile across the range of values, it is clear that in the case of both non-contact soft tissue injuries and all injury together that an acute:chronic value near the 75th percentile of 1.26 is likely to minimise the risk of injury, compared with the current median value across players of 0.82. Given this and in the absence of individualised acute:chronic workload thresholds, practitioners should aim to maintain an acute:chronic workload value greater than the currently observed median value to minimise injury risk.

In rugby union, only two previous studies have examined the relationship between training load and injury risk, with just one reporting a measure accounting for both duration and intensity (Cross et al., 2016b), and the other study examining training volume alone (Brooks et al., 2008). The work of Cross et al., (2016b) demonstrated an unclear association between the acute:chronic workload ratio (termed training stress balance in the paper) and injury risk and called for further data to be collected to confirm the utility of the measurement in rugby union. This PhD has addressed some of the other limitations of previous work by capturing pre-season load as well as accounting for other risk factors including previous injury, which was not accounted for by Cross et al. (2016b). The inclusion of pre-season loads experienced by players is important in the context of understanding risk, as it has previously been shown that increases in pre-season participation can decrease the risk of injury as well as decrease the percentage of games missed in-season (Windt et al., 2016). Given that injury is multifactorial, the inclusion of previous injury alongside other covariates addresses the absence of such information in the modelling used by Cross et al.(2016b). Previous injury has been demonstrated as an important risk factor for injury in not only previous work in rugby union (Quarrie et al., 2001; Cross et al., 2015; Williams et al., 2017c), but in the present study also, with each new injury over a 12 month period increasing the risk of a subsequent non-contact soft tissue injury (Table 6.5) and any type of injury (Table 6.3).

Prior to the investigation of the relationship between the acute:chronic workload ratio and injury risk, each of the covariate risk factors deemed as having a potential influence over this relationship were examined for isolated links with injury risk using univariate generalised linear mixed models. Variables from this process, followed by a backwards stepwise elimination process, were then included in multivariate models. This process was undertaken to establish the key variables which may substantially moderate the load-injury relationship (Windt et al., 2017; Colby et al., 2017). What was clearly evident from undertaking this process was that modelling of risk factors in a univariate way did not represent the same risk as when other covariates had been adjusted for. For example, in the case of both the all injury analysis as well as the non-contact soft tissue analysis alone, the effect of each covariate on injury risk changed. In the case of previous injury, this risk factor appeared of greater importance for subsequent non-contact soft tissue injury than that of all injury types. The greater importance for subsequent non-contact soft tissue injury over all injury types may be due to the nature of the type of injury. Injurious events occur as a result of a load in excess of that which can be tolerated by a tissue under normal circumstances or as a result of reduced tolerance levels to a point at which normal mechanism loads cannot be tolerated (McIntosh, 2005). After an extended period of time away from competitive match play due to injury, medical staff are required to assess an athlete’s readiness to return and must consider a myriad of factors as outlined in Blanch and Gabbett, (2016). Should return to sport occur too soon with insufficient recovery time for the affected tissue, the potential for an athlete to enter a cycle of chronic rehabilitation is possible (Gabbett, 2016a). A greater importance must, therefore, be placed on these injury types to ensure that full recovery has occurred prior to return to sport, which may minimise the risk of recurrence of a potentially more controllable injury type that that associated with contact. Furthermore, given the difficulty in predicting and preventing contact related injuries in rugby union, special emphasis may be placed in monitoring programmes on targeting the non-contact soft tissue type injury, for which a number of prevention programmes have previously been reported (Hislop et al., 2017; Attwood et al., 2017).

Previous work in rugby union has demonstrated a 60% rise in the risk of all injury in that season following a concussion (Cross et al., 2015). While this was supported in the context of univariate modelling, when adjusted for other risk factors, the effect of previous concussion on subsequent injury (any type) was reduced to a "*possibly*" harmful relative risk of 1.12 and in the case of non-contact soft tissue injury, a *"likely"* beneficial effect (Table 6.3 and 6.5). While these findings were unexpected, there are a number of possible explanations. In the work of Cross et al. (2015), concussion was the primary objective risk factor being examined with no measure of all previous injury included. Within this study, both concussion and all previous injury were included to identify the isolated risk associated with concussion, over and above that of all injury types. Given the potential that players with concussions were also represented within all previous injury, multicollinearity was assessed using VIF, which demonstrated low levels of multicollinearity. Therefore, the 60% increase in risk of all injury reported by Cross et al. (2015), may represent a proportion of the overall change in risk associated with having any previous injury; however, the survival analysis undertaken within the work of Cross et al. (2015) would indicate there is a unique effect of concussion at play, above that of other injury types. Although the mechanisms for the rise in subsequent injury after concussion are not known, Cross et al. (2015) suggested that this may be due to deficits in gait or impaired dynamic balance. A recent scoping review investigated some of the proposed mechanisms for this increase in risk, concluding that dual-task neuromuscular control deficits as well as other motor system and attentional deficits may persist after a concussion and contribute to the risk of sustaining a subsequent injury on return to full sports participation (Howell, Lynall, Buckley and Herman, 2018). Although these suggested mechanisms have yet to be experimentally tested, in the context of the current work, it is possible that these changes influence all injuries and not non-contact soft tissue injuries alone, given the high speed and high contact nature of rugby union, meaning impaired balance or gait may lead to incorrect positioning or awareness of opponents leading to subsequent injury, while attentional focus and narrowing vision field may also play a role in these injury types (Andersen and Williams, 1988).

The effect of match minutes as a univariate risk factor demonstrated a higher risk the more match minutes played. However, when adjusted for other covariates, the highest risk group for non-contact soft tissue or all types of injury were those having played less than 5.6 full match equivalents, with players in the upper two categories of match minutes, demonstrating either unclear (all injury) or beneficial effects (non-contact soft tissue injury). Previous work examining exposure to match minutes as a risk factor for injury in rugby union reported a higher risk of injury in players playing less than 15 games and over 35 games in a previous 12 month period; however, one of the limitations of this work was an assumed constant training load within each team (Williams et al., 2017c). The findings of the current study confirm the higher risk associated with a low exposure to match minutes with the potential reasons for this being either a player experiencing high injury rates and, therefore, little match exposure over the course of a season, or a lack of match fitness and physical robustness to cope with the physical demands of match play. In the context of the upper categories of match exposure being either unclear or beneficial, this may be the result of the opposite effect whereby within these groups, player availability is high throughout the season and, therefore, it represents a survivor cohort. While the inclusion of these covariates within the modelling process was to ensure the estimates around load were as representative and accurate as possible, what they have shown is the importance of multivariate modelling of risk factors when analysing injury risk.

Although the acute:chronic workload ratio is widely used in research as a load measurement tool, the use of acute and chronic loads as distinct risk factors has also been widely examined. In isolation, high acute workloads have previously been linked with an increased risk of injury in multiple sports (Piggott et al., 2009; Rogalski et al., 2013; Esmaeili et al., 2018; Hulin et al., 2014), including rugby union (Cross et al., 2016b). These findings were supported in the current study for all injury types, with higher acute loads associated with increased injury risk. This finding was not, however, seen looking at non-contact soft tissue injuries exclusively with only unclear associations demonstrated. In conjunction with the findings associated with the acute:chronic workload ratio, this suggests that although an athlete requires a regular training stimulus, to maintain moderate to high acute:chronic values, these values should not be achieved through large increments in acute load. Although high acute loads represent the greatest risk, given the desire for equal observations in workload categories (i.e. low, moderate low etc), the values associated with high workload span a broad range (378-2002 AU) and could perhaps be split based on arbitrary binning at certain values of interest. An association between chronic load and injury risk has also previously been documented, with conflicting results evident. While the body of research is suggestive of a protective effect of high chronic loads (Hulin et al., 2016a; Hulin et al., 2016b; Windt et al., 2016; Cross et al., 2016b), there is also evidence for an increase in risk associated with high chronic loads (Esmaeili et al., 2018). In the case of both non-contact soft tissue and all injury types in this study, moderate to high chronic loads (248-377 AU) demonstrated the highest risk of injury, with moderate to low chronic loads representing the lowest risk (158-247 AU). Similar to that of acute load, a spread of values existed in each category and it may, therefore, be of greater interest to set arbitrary cut points for more targeted analysis. Given the time frames over which these acute and chronic time periods were calculated is also a consideration, with the 3 and 14 day period used unlikely to be the same as those previously reported in this field, making direct comparison difficult.

This study has aimed to address as many of the current recommendations for analysing longitudinal training load data and injury risk, however, there are some limitations associated with the approach taken. The first limitation is in the use of just one measure of load, namely session rating of perceived exertion (sRPE). Although this method is widely used within the training load literature, and is a valid and reliable method for data capture (Haddad et al., 2017), it represents just one element of physical load, the internal load/ response. While it would have been advantageous to collect an external load metric in combination with sRPE, the heterogeneity in systems and definitions used as well as the variables collected across clubs for a metric such as Global Positioning Systems (GPS), would make inter club comparison of data difficult (Chapter Seven). Although a measure of both internal and external load would have been desirable, the choice to use sRPE alone reflected the call for use of the measurement tool in rugby union settings (Quarrie et al., 2016) as well as the evidence suggesting the strongest link between sRPE derived training load and injury risk, of all load measures (Eckard et al., 2018). A second limitation to the current study is the comparison between the acute:chronic load values reported here and those previously used. This comparison is difficult given the time frames over which they have been calculated. These dissimilar ways in which the acute:chronic values were calculated means that it is unclear whether differences in the risk profile of athletes across the range of acute:chronic workload values are due to differences specific to rugby union or to the calculation method. Despite this, the findings of the current study suggest a value of 1.26 to be lower risk than the currently observed median value, while also representing a value similar to previously used "sweet spot" values (Blanch and Gabbett, 2016; Gabbett, 2016a). Further to this, the rationale for the time periods used in this study are clearly defined and outlined in Chapter 5 and provide justification for use in the analysis of the load-injury relationship. The findings of this study, which show an increase in risk during periods of low acute:chronic load may be due to players carrying small injuries which do not prevent them from being selected for matches but may hamper their preparation for matches. Given that this study uses a 24-hour time loss definition (Fuller et al., 2007c) it is possible that there is no representation of injuries which may be limiting full participation but not removing the player entirely. The use of a tool such as the Oslo Sports Trauma Research Centre Overuse Injury Questionnaire may allow for the capture of such injuries and, therefore, establish if such an issue was present (Clarsen et al., 2013). Finally, in a recent paper, Carey et al. (2018) outlined the dangers associated with categorising data into discrete groups when making inferences about player injury risk. The main concerns reported were: 1. How reference groups were selected 2. Assumption of different risk based on grouping (e.g. two players with similar absolute values have very different risk values based on grouping) 3. The potential for error using discretised values. While these concerns are apparent within this study, they were controlled in the following manner: 1. In deciding reference groups, a clear justification was outlined *a-priori* and is outlined in the methods. 2. Although categorical grouping was undertaken, in the context of the main training load outcome, a polynomial curve was fitted to represent the data (Figure 6.1 and 6.2). This would allow individual comparison of injury risk at different cut points of the acute:chronic range. It is also recognised that in practice this relationship will be unique to each individual player, which will be dependent on load tolerance and, therefore, the average values represented in Figures 6.1 and 6.2 are only representative of the grouped relationship. 3. To minimise the risk of error, 90% CIs were used as a more conservative estimate of risk, while it was also shown by Carey et al. (2018) that increases in sample size reduced overall error. Therefore, given the associated sample size of this study and the use of more conservative confidence intervals, error should be minimised.

This study is the largest of its type and represents the first to show a clear relationship between the acute:chronic workload ratio and injury risk. The greatest risk of injury was evident at the lower end of acute:chronic workload ratio scale with current median values seen in clubs representing a value which is not optimal for minimising injury risk. Lower risk values were observed above the current median value reported and should be considered; therefore, as a strategy to minimising risk. This study has also demonstrated the importance of multivariate modelling of injury risk factors with the effects of some previously established risk factors changing after adjusting for other confounders. In conclusion, this study has demonstrated a clear link between training load and injury risk, with low acute:chronic values associated with a higher risk of injury in rugby union players. From a practical perspective, it is, therefore, recommended that players aim to maintain a regular training stimulus with acute:chronic values in the region of 1.26 being beneficial and likely to minimise injury risk.

CHAPTER 7

Athlete monitoring in rugby union: is heterogeneity in data capture holding us back?

7.1 Introduction:

The monitoring of training load in sport is undertaken to maximise the potential for performance while minimising the risk of injury (Akenhead and Nassis, 2016; Soligard et al., 2016). In recent years, there has been a proliferation in the use of technology in athlete management with practitioners across sport wanting to engage in a more scientific approach to monitoring their athletes (Halson, 2014). While the use of increasingly complex technologies is growing, the use of more simple and cost-effective monitoring tools is also apparent, including the session Rating of Perceived Exertion (sRPE) method (Comyns and Hannon, 2018). Session RPE is commonly used in rugby union as a monitoring tool for individual player internal load (Comyns and Flanagan, 2013). The potential utility of sRPE in the context of rugby union is evident given its ability to be used across multiple training modalities and its simplicity. Furthermore, it has also been shown that the tool is both reliable and valid when compared with other internal load measures such as heart rate and lactate (Coutts, 2009; Gabbett, 2004b). The use of sRPE has been documented in rugby union as widespread, with 95% (n = 20) of the coaches of professional teams reporting its use (Comyns and Hannon, 2018).

Of this cohort, 95% considered sRPE an effective method for use in the management of individual player load with 63% reporting the measure's effectiveness for injury prevention, 53% for illness prevention and 61% for enhancement of individual player performance.

Training load can be divided into two separate categories of load; internal and external. External load is the physical work prescribed in a training plan while internal load is the psychophysiological response of an athlete to that external load (Impellizzeri et al., 2019a). In the context of athlete monitoring, sRPE has been proposed and supported as one such measure of internal load and the response to training (Foster et al., 2001; Comyns and Hannon, 2018). Despite the widespread use of sRPE within rugby union, there is a desire amongst sports scientists and coaches to harness the power of newly available player tracking technologies to enhance player welfare and performance. In recent years the use of this technology has grown in the context of rugby union with extensive use amongst professional teams. However, although the use of global positioning systems (GPS) technology is widespread, there is little understanding as to how each individual club collects, aggregates, reports and utilises GPS data, and to what extent does methodological variation exist between clubs. To capture this information in the context of soccer, Akenhead and Nassis (2016) undertook a questionnaire of sports science/ medicine staff at professional football teams to understand more about their capture of training monitoring data. Of the 42 respondents, only 28 reported using sRPE, while all 42 reported the use of both GPS and heart rate to monitor their players. The main variables captured by clubs were accelerations, total distance, high speed running, metabolic power and heart rate. The majority of the analysis of monitoring data was done using Microsoft Excel, while clubs reported lack of human resources and coach buy-in as the two greatest barriers to use within their clubs. Interestingly, only 20% of the respondents found GPS an effective measure of performance with 23% considering the tool an effective measure for injury prevention. These findings are of particular interest given the widespread use of the tools as well as the time and money resources involved.

As the growth of GPS for athlete monitoring within rugby union continues, it is pertinent to understand how such data are collected, used and valued in this setting. Therefore, the aim of this study was to complete a survey of practitioners from each clubs in the English rugby Premiership to establish the principles of practice and the way in which GPS data are collected to establish whether there is consensus amongst clubs.

7.2 Methods:

Twelve members of staff were asked to complete the survey online, one from each club in the English Premiership (Appendix D). The respondents included five sports scientists, three strength and conditioning coaches, one head of athletic performance and three heads of strength and conditioning, and had a mean years' experience of 8 (±2) y. At the beginning of each questionnaire, a cover note was provided to the participants explaining the purpose of the survey and to provide an opportunity for questions regarding the study to be asked to the lead investigator. Further verbal communication was undertaken with each of the participants of the questionnaire prior to distribution to ensure each participant was aware of the study requirements and purpose. Prior to the start of the survey, each participant was asked to provide consent for the study using a tick box at the end of the information page. Only once a participant had provided informed consent did the questionnaire populate with questions that were visible to the coaching staff. The study obtained ethical approval by the Research Ethics Approval Committee for Health (REACH) prior to the survey being distributed (Ref: 15/16 252).

The survey was reviewed by each member of the research team and changes regarding the content, structure and lay out of the survey were made to ensure all necessary information was obtained. The questionnaire was then trialled by one member of sports science staff at another professional rugby club to assess the readability and content of the questionnaire. Following feedback from this process, the questionnaire was sent to the 12 clubs participating in the English Premiership (the top domestic rugby union league in England). The final version of the survey comprised of 25 questions (Appendix D). The first section contained questions regarding which monitoring tools were used by clubs to manage individual injury risk as well as the relative importance of each of those measures (Question 4). Section 2 included a series of questions about the use of

GPS monitoring exclusively. This section required answers concerning the GPS system, version, unit type, software, measurement speed, metrics captured and relative importance of GPS for injury management and performance assessment. Finally, the remaining questions concerned the operational definitions used by clubs for variables such as high-speed running, as well as information regarding the barriers to using GPS within their individual team settings. The questionnaire took between 5 and 10 minutes to complete and was distributed to the respective staff members via email. If, within one week, no response was received a reminder email was sent to the staff members. All 12 of the clubs had a member of staff respond to the survey. The survey was designed and distributed using Bristol Online Surveys (now www.onlinesurveys.ac.uk). Data was collated and exported into a Microsoft Excel CSV file for analysis by the primary investigator. All data was presented as either median and interquartile ranges or frequencies of response, dependent on the nature of the question asked.

7.3 Results:

7.3.1. Tools for injury risk management

To first establish the importance of a range of measures for injury risk management each participant was asked to rank from 1-5 the importance of each measure outlined in Figure 7.1, with 5 representing a variable deemed "highly valued" and 1 representing "not at all valued". All variables, with the exception of collision counts, player age and player experience, demonstrated a wide range of values with at least one club giving a value of 1 (not at all valued) and one giving a value of 5 (highly valued). Previous injury history was deemed the most valuable measure with a median response of 5, while GPS measures, collision counts, and player age were the joint second most valuable tools, with a median of 4. All other measures carried a median of 3.

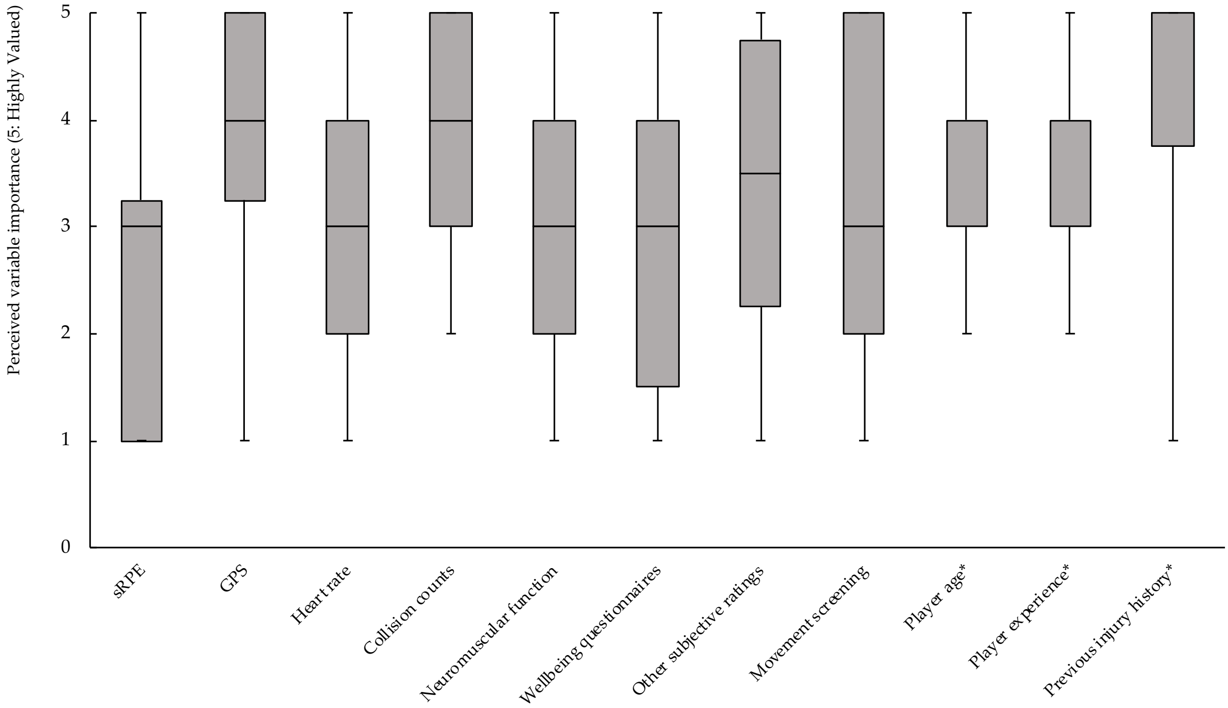

Figure 7.1**:** Box and Whisker plot showing the median, interquartile range and range of values associated with responses to the question: "On a scale of 1-5, how highly do you value the following measures for the management of individual injury risk (where 5 represents highly valued and 1 represents not at all valued)". Grey boxes demonstrate the median and inter quartile range while the upper and lower end of the whiskers represent the lowest and highest observation. Variables exhibiting an asterisk demonstrated the same median and upper quartile values; therefore, the median is not visible.

A second question was asked of the participants, which aimed to further understand the importance of GPS measures in the management of not only injury risk but also individual player performance. The results of this question are shown in Figure 7.2 and demonstrate the overall relative importance of GPS metrics for managing individual injury risk compared with the assessment in performance (median of 8 vs 6). Further to this, there was a wider spread of values associated with the use of GPS as a performance assessment tool (range: 1-10 vs 3-10 for injury risk management) with one participant deeming it not at all useful.

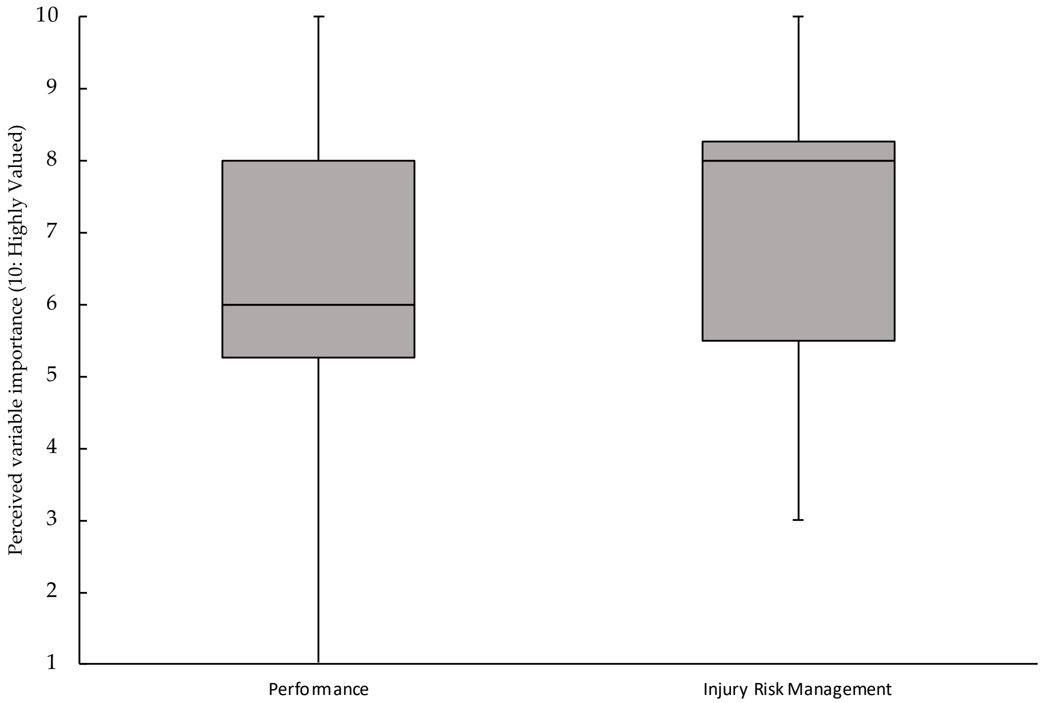

Figure 7.2**:** Box and Whisker plot showing the median, interquartile range and range of values associated with responses to the question: "On a scale of 1-10, with 10 being the most important, how much do you value GPS data as a measure of player performance/ individual injury risk management?". Grey boxes demonstrate the median and inter quartile range while the upper and lower end of the whiskers represent the lowest and highest observation.

7.3.2. GPS collection methods

To capture further information about the GPS measures collected and used by clubs, each participant then responded to a series of question outlining information specific to their GPS use. Eighty-three percent (10/12) of participants reported using the CATAPULT system, while 16% (2/12) reported the use of STATSports. This can be broken down further to the Optimeye x4 (16%: 2/12), Sprint (16%: 2/12) and Openfield (50%: 6/12) versions for CATAPULT users and the APEX system for the STATSports users (16%: 2/12). Twenty five percent of respondents used the x4 CATAPULT GPS units, while 58% used the S5 units. Both STATSports users had recently changed to the APEX units. A wide variety of computer software was used to analyse the GPS data with a large number of clubs using more than one software type. These included Openfield (33%: 4/12), Excel (42%: 5/12), Sportscode (8%,1/12), Sprint (16%: 2/12) and APEX (16%: 2/12). The majority of clubs used units that were capable of 10 Hz recording speeds (92%: 9/12) while one team used 15 Hz units. The median number of units per team was 38 units with a range of 15 to 53. Only 42% (5/12) of clubs reported having enough GPS units to measure all players, while 33% (4/12) collected data for all senior players (non-academy) and 25% of respondents collected data for key players only. A question regarding barriers to data collection was also included. The most commonly reported barrier was the validity and reliability or GPS units (42%: 5/12), followed by lack of equipment (33%: 4/12), lack of staff to deal with the volume of data (16%: 2/12), lack of coach buy-in (16%: 2/12) and a lack of consensus on best practice in GPS use (16%: 2/12). Further to these, 33% (4/12) of clubs reported no barriers to GPS data collection and one club reported "time to analyse data" as a barrier.

7.3.3. GPS measures utilised

A wide variety of measures are collected across teams (Figure 7.3) with the most commonly collected being distance in speed zones, and high-speed running distance in particular (100%: 12/12). Total distance was the next most commonly captured metric (92%: 11/12), followed by a count of sprints and meters per minute (83%: 10/12). Of the metrics collected, 42% (5/12) reported high-speed running as the most important metric for the assessment of performance, 25% (3/12) used metres per minute, 16% (2/12) reported total distance and 8% (1/12) reported the number of sprints. Twenty-five percent (3/12) of respondents did not provide an answer to this question. In the management of injury risk, high speed running was deemed the most important variable for 42% (5/12) of participants, followed by total distance (33%: 4/12) and accelerations/decelerations (8%: 1/12), with 33% (4/12) stating a combination of measures.

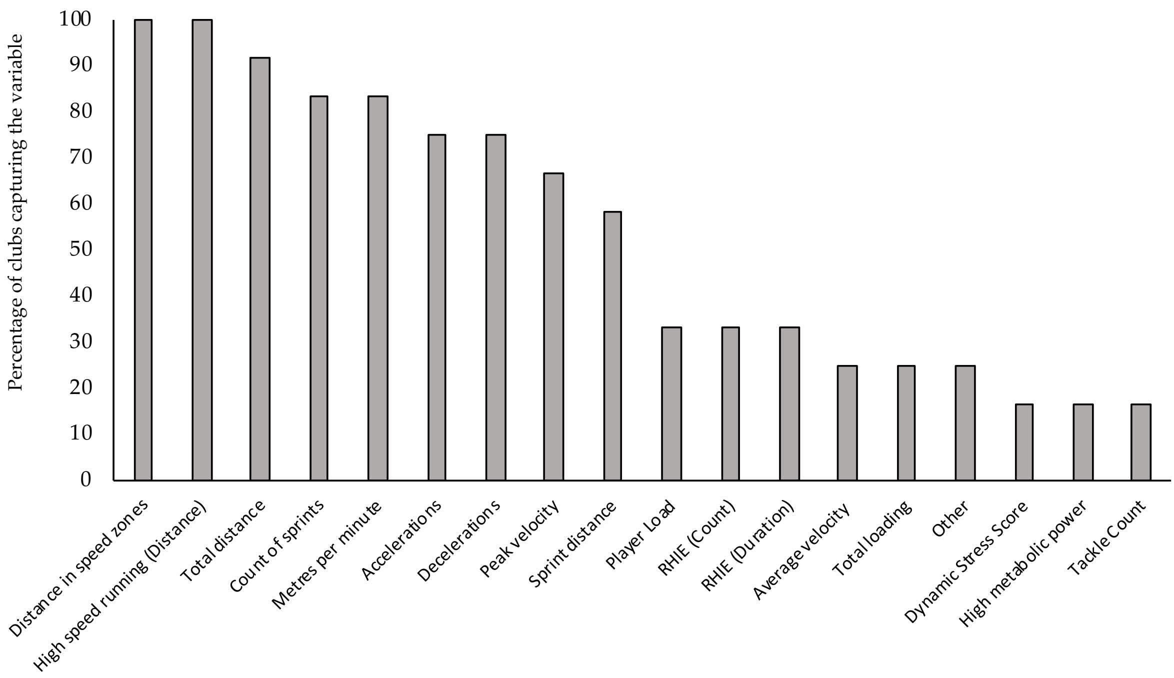

Figure 7.3**:** (x-axis) GPS metrics captured and (y-axis) percentage of teams recording these metrics. RHIE, Repeated high intensity efforts.

GPS measures can be collected in absolute terms (standard across all players, e.g., 5 m/s high speed running) or relative terms (individual to each athlete, e.g., 70% of that player's max velocity [Vmax]). In training, 33% (4/12) of respondents reported that measures were collected using absolute values, while 8% (1/12) of participants used relative measures only: 58% (7/12) recorded both relative and absolute. During matches, there was an even split between absolute and both measures being used with 50% (6/12) of participants using each. The measure high-speed running, which was reported as important for both the assessment of performance (42%: 5/2) and management of injury risk (42%: 5/12), was captured as an absolute value by 25% (3/12) of participants, relative by 58% (7/12), and both by 16% (2/12). For those reporting the use of an absolute high-speed running threshold, the values used were >5 m/s or >5.5 m/s, whereas in the relative group, values of 40-70% of Vmax, >49% of Vmax, >50% Vmax, >60% of Vmax, >70% of Vmax, >80% Vmax were used. In the classification of sprinting, absolute values of >6.7 m/s, >7 m/s and >7.5 m/s were used as well as relative values of >70%, >80% and >90% of Vmax. When asked if contact was captured during matches, 75% (9/12) reported that they did capture contact in games, while 25% (3/12) said they did not: this was measured using video analysis (66%: 8/12) and GPS (16%: 2/12).

7.4 Discussion:

In the current monitoring practices of professional sports teams there are a myriad of variables considered to be important for managing individual injury risk. While previous injury was determined to be the most highly-valued measure for managing injury risk, GPS metrics were outlined as the most important monitoring tool for conditioning staff. Despite this, it was clear that the methods of data collection, barriers to implementation of monitoring, definition of key variables and relative importance of metrics for performance assessment and injury risk management varied between clubs. This variation extended to all monitoring metrics with almost every measure being considered as "not at all valued" by one club and "highly valued" in another. This study presents an overview of the monitoring practices of professional rugby union clubs as well as definitions, methods, utility and perceived effectiveness of GPS metrics in the management of player welfare and tracking of player performance.

Injuries in sport have repeatedly been shown to produce negative consequences for team success (Hägglund et al., 2013; Williams et al., 2015; Drew et al., 2017c) and, therefore, minimising the risk of injury is a key task for sport scientists, team medics and strength and conditioning coaches. In rugby union, a number of risk factors have previously been shown to be associated with injury risk, including: previous injury (Cross et al., 2015; Williams et al., 2017c); player age (Quarrie et al., 2001); functional movement competency (Attwood, Roberts, Trewartha, England and Stokes, 2018); and player load (Cross et al., 2016b; Williams et al., 2017c). Despite this, there is little known about how widely these measures are used in the individual management of injury and how they are valued amongst practitioners in an elite context. In this study, previous injury was deemed to be the most important risk factor with a median value of 5 (the highest possible score), which represented a "highly valued" measure (Figure 7.1) Although collision counts represent the next most highly valued measure (alongside GPS and player age: median score of 4), the capture of this metric is primarily reliant on time consuming video analysis (66%: 8/12), whilst only 16% (2/12) of respondents used GPS-derived metrics to capture collision metrics. Interestingly, despite the reported widespread use of the sRPE monitoring tool (Comyns and Hannon, 2018), the measure represented one of the lowest scoring tools, with a median response of 3, however values ranged from 5 (highly valued) to 1 (not at all valued). These values would appear to indicate the favorability of GPS derived metrics for training load management over sRPE in the context of rugby union, despite the limited ability of GPS technology to fully represent the external load demands placed on athletes in collision sports due to the large amount of contact based activity with little horizontal displacement (Boyd et al., 2013). Further to this, the apparent favorability of external metrics comes in spite of recent work outlining the importance of internal loads in determining training outcome and thus the importance of these measures for athlete management (Impellizzeri et al., 2019a). With the advent of these newly available technologies, it appears that conditioning staff have been attracted to increasingly complex technologies to manage individual player injury risk, with this coming in spite of the concerns raised over the validity of the measures as well as the time intensive nature of its use. The attractiveness of this technology and the fear of being 'left behind' has potentially led to a belief that complexity (from a functional perspective, not a usability one) provides more favorable outcomes, which may not be the case if data quality is compromised for data quantity. Despite this, it is clear that GPS technology has established itself as an important tool for practitioners in professional rugby union, with coaching staff reporting a perceived greater effectiveness of GPS technology in the management of individual injury risk (median of 8) compared with the measurement of performance measurement (median of 6: Figure 7.2).

With the advancement of GPS technology alongside the integration of tri-axial accelerometers into these units the number of metrics available is extensive, allowing practitioners to use only those that they deem most applicable and relevant for them. Of the numerous available metrics, distance in speed zones and high-speed running were reported as the most commonly collected, with high speed running of particular interest. This metric can be recorded as a relative or absolute measure, with 58% (7/12) using relative measures, 25% (3/12) using absolute measures and the remaining 16% (2/12) using both. Of the relative measures, six different definitions of high-speed running were used, including; 40-70%, >49%, >50%, >60% >70%, and > 80% of a player's max velocity. Definitions of over 5 m/s and 5.5m/s were used for absolute measures. These findings demonstrate the substantial variation that exists between clubs when measuring what is considered the same GPS metric. In professional rugby union, running is the third most common mechanism of all injury, while running is also the most common mechanism of hamstring injury (Kemp et al., 2019). Given that hamstring injury is the most common training-related injury and given also, that training is deemed a more "controllable" environment for injury prevention strategies compared to match play, this may offer a reason as to why high-speed running is considered so important in the management of individual injury risk. Current evidence suggests that a relationship between high speed running load and injury exists (Gabbett et al., 2012; Duhig et al., 2016; Malone et al., 2018), while it is also documented that well-developed physical qualities such as intermittent aerobic fitness may offset injury risk associated with rapid increases in high speed running (Malone et al., 2018). Knowing this, the monitoring of high-speed running within team-sports has become widespread to minimize the risk of a potentially more controllable injury mechanism than that of contact.

While the use of GPS data (in particular high-speed running) to measure performance is unlikely to be of huge benefit in rugby union, it may offer a surrogate measure to represent the ability of players to reach full speed, such as a line break or covering defensive tackle. In rugby league, faster speeds over 40m has been associated with a higher number of tries scored (Gabbett, Jenkins and Abernethy, 2011), meaning the capture of such metrics may offer insight into player performance. It is likely, however, that key performance indicator metrics provided by statistic providers will offer a greater insight into player performance than GPS metrics alone. The next most commonly collected variables were total distance (92%: 11/12), count of sprints (83%: 10/12) and metres per minute (m/min) (83%: 10/12). These variables represent only a small proportion of the 17 that were provided in the questionnaire as well as several "Other" answers provided by the respondents. When asked to consider the importance of these variables for the purposes of performance assessment, high speed running was deemed the most important by 42% (5/12) of respondents while m/min was reported by 25% (3/12) of respondents. In the case of injury risk, high-speed running was deemed the most important variable (42% of respondents: 5/12) followed by total distance (33% of respondents: 4/12). This is consistent with previous work (Akenhead and Nassis, 2016), and may be considered unsurprising given the more neuromuscular-orientated load associated with this type of exercise (Buchheit and Simpson, 2017).

In the English Premiership competition, England's highest level of club rugby, there are 12 clubs located across the country, each of which select, capture and utilise whichever monitoring methods they deem most appropriate to best manage their players. To gain insight into the systems, providers, and methods used by clubs, the questionnaire requested the details surrounding the use of GPS so as to guide the project in targeting a group of clubs collecting and using similar data, to avoid comparison across differing systems. Of the 12 clubs, 83% (10/12) used the CATAPULT provider for their data collection. Although differences existed between unit types, each of the clubs using CATAPULT had monitors capable of recording at speeds of 10 Hz. On average, each club had 38 units at their disposal to capture GPS across their playing squad (mean and SD squad size; 57 ± 5); however, this ranged from 15 to 53 units between different clubs, with four clubs stating a "lack of equipment" as a barrier to implementation.

Interestingly, the most commonly cited barrier to further implementation or use of GPS data were issues concerning the validity and reliability of GPS data. These findings suggest that despite extensive work examining the validity and reliability of these measures as well as a number of systematic reviews (Varley et al., 2012; Scott et al., 2016), there is still concern amongst practitioners regarding GPS technology use in rugby union.

One of the criticisms of GPS technology in the quantification of external loads in collision sports is the potential for underestimation of demands due to the potentially large amount of impact activities with little horizontal displacement, including tackling, mauling and rucking (Boyd et al., 2013). Concerns raised over the validity and reliability of GPS data that was evident within the current questionnaire may be related to these criticisms over the capture of collision data. Despite these concerns, a 2016 study (Roe, Halkier, Beggs, Till and Jones) has demonstrated good agreement between accelerometer derived metrics Player Load, Player Load 2D and PLslow and manually coded collisions, concluding that practitioners can confidently use accelerometer based metrics to quantify these aspects of play, in particular PLslow. While these findings are promising for the detection of collisions in games, differences between GPS systems and the youth population used in this study may limit the generalisability of the findings. In addition, the differentiation between different contact events would be useful, as opposed to the summation of all collision events. To ensure the validity and reliability of such measures in the context of one's own club, it is encouraged that such validation studies are undertaken, to not only ensure the quality of data collected but also confirm or refute the findings of this study in an adult population. While such studies demonstrate the validity and reliability of contact-derived training load metrics, it is evident that this has not gained support within the elite club setting with only 2 clubs using GPS derived contact metrics and 42% (5/12) clubs outlining concerns over the validity and reliability of the units. Finally, when asked about the methods used in data collection by clubs, there is a lack of consensus with regard to the definition of specific GPS metrics, for instance high-speed running. Within this cohort two different definitions used when measuring the metric in an absolute manner and 8 different definitions when measured in a relative manner. This finding is supported in the work of Cummins, Orr and West (2013), who reported a lack of consistency in the reporting of speed zones and called for a consensus to be reached to aid comparison of demands within sports.

While this study offers valuable insight into the methods used and perceived importance of monitoring metrics in professional rugby union, there are a number of limitations associated with the study. Despite capturing the opinions of one staff member across each of the clubs in the league, not only does this provide a relatively small sample size but also the views expressed may only represent that of the conditioning staff within the club, and the utility of monitoring metrics may be of different value to medical or other coaching staff. Another limitation concerns the possible answers that coaches could give within the survey. Although an “Other” option was given as an answer choice with a text box to elaborate, not all staff members availed of this option and, therefore, the use of qualitive interviews may offer more detailed insight in future studies. Finally, while these responses were representative of the staff at the time of answering, given the ever-evolving monitoring landscape, opinions and the relative importance of these metrics may have changed with the improvements in technology.

The current study documents the tools, methods, and perceived value of monitoring variables collected by rugby union teams, in particular GPS technology. While this type of work has previously been undertaken in soccer (Akenhead and Nassis, 2016) as well as in relation to sRPE specifically in rugby union (Comyns and Hannon, 2018), this is the first to outline the relative importance of different monitoring variables in the context of performance measurement and injury risk management in rugby union. The current study also provides insight into the importance placed on GPS metrics by clubs, as well the methods used to collect this data. What is clear from this questionnaire is that there is no consensus on best practice for GPS data collection in rugby union, with multiple definitions being used to collect the same variables. This study also highlights some of the difficulties associated with collecting this type of data, including lack of equipment, reliability and validity of the data, and the staff required to deal with the volumes of data. Furthermore, this study outlines the wide variation in the relative importance placed by practitioners on certain metrics for injury risk management and performance measurement, with nearly every measure being highly valued in one setting but deemed “not at all valued” in another. What is apparent from the current landscape in elite rugby union is that although the technological advancements associated with GPS use have made athlete monitoring more precise, the introduction of these increasingly complex methods of data collection may limit positive outcomes in athlete management until extensive work is undertaken to align and better understand how these metrics relate to individual injury risk and performance. Moving forward, for practitioners and researchers to maximise the value of these new technologies, consensus on the best available methods for data collection should be produced. Attaining such a consensus would reduce the burden on conditioning staff for the collection, analysis and synthesis of such information, while also minimizing the number of potential data collection points required from athletes daily. Alongside this, given the range of resources available to elite rugby union practitioners to capture monitoring data, a minimum standard for athlete load monitoring should be suggested to ensure key elements of both external workload and internal response of athletes are captured.

CHAPTER 8

Managing injury risk with training load in rugby union: Does combining measures of internal and external load trump either in isolation?

8.1 Introduction:

The construct of "load" represents multiple stressors imposed upon an athlete, with these loads ranging from psychological, social or physical in a broad sense, to more focused loads such as injury management and performance analysis (Quarrie et al., 2016). The physical loads imposed upon athletes are considered to be modifiable and the management of these loads is an increasingly popular injury risk mitigation strategy in both recreational and professional sport (Drew and Finch, 2016; Jones et al., 2017; Eckard et al., 2018). In the context of this thesis, physical load represents "the cumulative amount of stress placed on an individual from multiple training sessions and games over a period of time" (Gabbett et al., 2014). Physical loads can be further categorised into external and internal loads with the former outlined as the external stimulus applied an athlete (independent of their individual characteristics), and the latter described as the physiological or psychological responses of the athlete to the external stimulus (Impellizzeri et al., 2005; Soligard et al., 2016).

Internal load can be measured using a number of measures including session Rating of Perceived Exertion (sRPE) (Foster, 1998) and heart rate (Banister, 1991). External load can be measured using sports specific event counts, such as the number of balls bowled in cricket (Dennis et al., 2003), or, commonly in modern sport, Global Positioning System (GPS) metrics (Cunningham et al., 2018; Reardon et al., 2017). In rugby union, the use of both sRPE and GPS are commonplace in daily monitoring to inform decisions about injury risk management and performance (Comyns and Hannon, 2018). Despite both sRPE and GPS providing useful information to a practitioner, both have apparent strengths and weaknesses, with sRPE criticised for its inability to isolate specific perceptual demands of different training modes (McLaren et al., 2017), and the validity and reliability of certain GPS measures being questioned (Buchheit et al., 2014). Although both measures are widely collected in rugby union, the metrics associated with GPS measurements appear more valued in the professional game, compared with sRPE (Chapter Seven). However, recently Impellizzeri et al. (2019a) warned against placing too great an emphasis on external load metrics, given the same external load applied to two separate athletes, or even to the same athlete under different environmental conditions, may elicit a different psychophysiological response. Given that internal loads have been described as the ultimate determinant of the functional outcome of training, collection of internal loads has been theorised as advantageous (Impellizzeri et al., 2019a). However, it has also been demonstrated that capturing external load allows for more precise prescription of further external loads (Impellizzeri et al., 2019a). Therefore, in isolation a measure of either the internal or external load can provide useful information, but it may be desirable to capture a measure of both types of load to fully understand an athlete's current fitness/fatigue status.

The link between workload and injury risk has previously been demonstrated across multiple sports using both internal (sRPE) loads (Rogalski et al., 2013; Colby et al., 2017; Esmaeili et al., 2018); and external (GPS) measures (Colby et al., 2014; Hulin et al., 2016a; Murray et al., 2017a). A wide range of GPS-derived metrics can be recorded, but two well-established and widely collected metrics are total distance (TD) and high speed running (HSR) (Chapter Seven), with high speed running in particular shown to be associated with changes in injury risk (Duhig et al., 2016; Malone et al., 2018). Regardless of the measures used in monitoring practices by professional sports teams, once a measure is captured, the methods by which it is aggregated and analysed must also be chosen. One such method for analysing workload data is that of the acute:chronic workload ratio. Historically a 7-day acute and 28-day chronic time window have been used to calculate this variable, although it has been suggested that other time periods may be more appropriate (Chapter Five, Carey et al., 2017a). Further to this, the use of exponentially weighted moving averages in acute:chronic workload ratios have been reported as more sensitive to injury risk when compared to the use of rolling averages (Williams et al., 2016b; Murray et al., 2017a). To optimise the utility of this data therefore, it is prudent to establish which of these measurement types are best associated with injury risk, as well as to understand how this might change depending on the training load variable of interest. Further to this, given the potentially important moderating effect of other injury risk factors such as age, position, previous injury, previous concussion and cumulative match minutes, establishing the relative importance of these risk factors when measured in combination with training load is also prudent (Windt et al., 2017).

Building on the work undertaken through Chapters One to Seven of this PhD thesis, the aim of this chapter is to compare and contrast the relationships between injury risk and three different training load measures. The selected measures [sRPE, total distance (from GPS unit) and high speed running distance (from GPS unit)] were chosen due to not only the clearly stated evidence for their association with injury risk but also given the widespread collection of these variables and relative importance placed on these by conditioning staff within professional rugby union (Chapter Seven). The aim of this chapter is, therefore, to assess the association between training load and injury risk using multiple training load collection measures. This chapter also aims to establish whether combining more than one of these training load measures provides more insight into athlete injury risk than any one measure in isolation.

8.2 Methods:

8.2.1 Participants

This study used an observational cohort design, capturing training load and injury data from 6 professional English rugby clubs. Following the completion of a survey of clubs to identify comparable data across all clubs involved in the Premiership competition (Chapter Seven), a group of 10 clubs were identified as using the same GPS provider (CATAPULT), who were subsequently approached for inclusion in the study. Inclusion criteria for the study dictated that clubs must be collecting training load data as part of current practice in the form of both session Rating of Perceived Exertion (sRPE) as well as both total distance (TD) and high-speed running distance (HSR) Global Positioning Systems (GPS) metrics. Eight of the 10 identified clubs fulfilled these criteria, with two of these eight clubs opting to not provide data for the study. The 6 clubs included in the final sample provided full datasets of both injury and training load data (minimum of 100 consecutive days per player involved) for a total of 363 unique players over the 2017-18 season. The study was approved by the University of Bath Research Ethics Approval Committee for Health (Ref no. 15/16 252).

8.2.2 Procedures

Injury data was captured by club medics using an online data capture platform (The Rugby Squad, The Sports Office UK Ltd.). For the purposes of this study, a 24 hour time-loss injury definition was used and was defined as “an injury that resulted in a player being unable to take a full part in future rugby training or match play for more than 24 h from midnight at the end of the day the injury was sustained” (Fuller et al., 2007c). Training load data was captured as part of normal practice within the clubs using the sRPE method outlined in Chapter Five (Foster et al., 2001). Match minutes were recorded using an online data capture platform (“Elitehub”, RFU, 2019), with match minutes on a given day multiplied by 10 to obtain match sRPE values. RPE values of 10 were used as it was deemed that players were likely to be maximally exerting themselves during game play, as well as the majority of players recording values of 9-10 on the sRPE scale in previous work (Cross et al., 2016b). GPS data was captured using CATAPULT GPS units (5/6 using S5 units, 1/6 using X4 units). Each club was asked to provide both a measure of total distance (TD) and high speed running distance (HSR) which all clubs collected, as identified in Chapter Seven.

Total distance was collected using a standard measure across each club, while variation existed between each club as to the HSR metric collected. The HSR variable was shown to be highly valued for managing player injury risk and assessing player performance (Chapter Seven). Given this, and despite the differences in HSR definition, rather than exclude the measure, HSR was recorded as defined by each club. Five of the six clubs used relative HSR values, derived from a player's maximum velocity (4/5) or maximal aerobic speed (1/5). The remaining club used an absolute value of HSR, set at >5m/s.

As per Chapter Six of this thesis, five previously documented injury risk factors were captured; these included player age, player position, previous injury in the preceding 12 months, previous concussion in the preceding 12 months and match minutes played in the preceding 12 months. Reference categories for covariates to allow for analysis between groups were set using the same criteria as outlined in Chapter Six. These reference categories were: Age- Lowest group, 18-22; Position- Back three; Previous Injury- 1 previous injury; Previous Concussion- no previous concussion; Match Minutes- Mod Low group, 297-665 or 3.7 to 8.3 full match equivalents. For acute and chronic loads, "moderate low" groups were used as reference categories, with each acute or chronic quartile split to have an equal number of observations in each group. All injury types were included as the outcome measure in this study.

8.2.3 Data Analysis

All data were collated into a final dataset representing each player on each day of the season with a corresponding injury indicator (binary 1/0 code to identify days on which injury occurred), load and covariate risk factor values for each day. To assess the best way to calculate an acute:chronic workload ratio derived training load measure, a number of calculation types were assessed including rolling versus exponentially weighted averages as well as 3, 5, 7, and 9 day acute loads and 14, 21, 28, and 35 day chronic loads (Williams et al., 2016b; Carey et al., 2017a). These calculations were assessed using coupled values (including the acute period in the chronic period) only as the work of Chapter Five demonstrated little empirical support for the use of uncoupled loads. The best fitting methods for acute:chronic workload calculation were assessed using Akaike Information Criterion (AIC) and Area under the curve (AUC), with the best models selected for inclusion in the final dataset.

A similar data analysis approach was undertaken to that used in Chapter Six with a three-stage analysis used. Initial independent univariate analyses of the previously identified risk factors (age, position, previous injury, previous concussion, match minutes) were undertaken in isolation to identify whether at least "*likely*" associations with injury risk existed. This was undertaken using the "glmer" function of the "lme4" package (Bates et al., 2018), with fixed effect terms as each covariate, random effects for each player nested within each individual team, and a complimentary binomial loglog-link term. As per Williams et al. (2017c), MBIs were used to assess the importance of the model outcome, which are based on effect size and corresponding confidence intervals (CIs) in relation to a smallest worthwhile change with thresholds for benefit and harm set as hazard ratios of 0.90 and 1.11 respectively (Hopkins, 2010). Unclear effects were reported if 90% CIs crossed both the threshold for harm and benefit by >5% (Williams et al., 2017c). Clear effects were termed as beneficial, harmful or trivial (less than the smallest worthwhile change), with the strength of the effect classed using a qualitative probabilistic term using the following thresholds: <0.5%, most unlikely; 0.5-5%, very unlikely; 5-25%, unlikely; 25-75% possibly; 75-95%, likely; 95-99.5%, very likely; >99.5%, most likely (Hopkins et al., 2009). Covariates demonstrating at least a "*likely*" association were retained and entered into a multivariable backwards stepwise elimination process of fixed effects in a generalised linear mixed model using the "GLMERSelect" function of the "Statistical Models" package (Newbold, 2019), in order to identify the most parsimonious model. The covariates retained by this process were then included in a final model, which assessed all injury risk alongside each covariate as well as a measure of acute load, chronic load and a change in load (i.e. the acute:chronic workload ratio) as previously outlined by Williams et al. (2017a). The analysis was undertaken for each of the three training load variables recorded (sRPE, TD, HSR), with the acute:chronic workload variables analysed at quintile values to aid interpretation of injury risk at percentile ranges from 0-100. Alongside each variable being analysed in isolation, acute:chronic workload ratio values for each of the three measures were included in the same model, with sRPE acute:chronic values included as the fixed effect of interest and the acute:chronic values for TD and HSR included as covariates; therefore, adjusting for a combination of internal and external load measurements. This was undertaken to identify whether the addition of multiple metrics added substantial value to the model in its ability to identify injury risk. Finally, an assessment of the sRPE variable using 7 and 28 days acute and chronic time periods was undertaken as a sample analysis to identify whether the relationship between load and injury was being driven by the methods used to calculate the acute:chronic workload ratio or whether the risk profile was the same, irrespective of the time periods used. Injury risk was expressed as the injury hazard (risk per player per exposure day), with comparisons between groups expressed as hazard ratios with 90% confidence intervals (Esmaeili et al., 2018). Confidence intervals were set at 90% to allow for the possibility that the true value lies 5% either below the lower limit or above the upper limit (Batterham and Hopkins, 2006). All analysis was undertaken using RStudio (RStudio, Inc. Version 1.1.463).

8.3 Results:

Of the 725 players registered across 12 clubs during the 2017-18 season, a total of 363 players across 6 clubs were included in the study. These players met the inclusion criteria for the study with complete datasets of injury information and a minimum of 100 days training load data. A total of 885 time-loss injuries were sustained over the data collection period for the 363 included players.

8.3.1 Acute:chronic workload ratio calculation methods

The assessment of best fit calculation methods was undertaken for each training load variable (sRPE, TD, HSR) in isolation, with both AIC and AUC values assessed. Across all three training load variables, the AIC and AUC values reported differing 'best fit' calculation methods. Given this, the values associated with AUC were selected as the primary model selection tool, given its previously documented use in studies of this type (Colby et al., 2017), as well as the desire to distinguish between injured and not injured players, as opposed to model fit necessarily. In the case of all three training load metrics, acute:chronic values calculated using exponentially weighted averages using acute periods of 3 days and chronic periods of 14 days represented the best model fit when analysing injury data (Figure 8.1). The AUC values associated with each of the three variables were similar, with sRPE and TD represented the highest AUC value (0.57), with HSR being the lowest value (0.55). The use of an acute:chronic workload ratio calculated using an exponentially weighted average over 3 to 14 day periods was, therefore, used for each variable and added to final modelling procedures.

8.3.2 Univariate Analysis and backwards elimination of fixed effects in generalised linear mixed models.

Univariate analysis of age, position, previous injury, previous concussion and match minutes was undertaken to identify covariates associated with a "*likely*" change in injury risk. Of these variables, age was the only risk factor not to demonstrate at least "*likely*" changes in injury risk, and was removed from further analysis (Appendix G). Position, previous injury, previous concussion and match minutes all demonstrated at least "*likely*" effects and were, therefore, entered into a generalised linear mixed model and put through a backwards elimination of fixed effects process. This process was completed for each training load variable, which in each case removed the position and previous concussion covariates, retaining previous injury and match minutes for inclusion in final modelling alongside the acute:chronic workload ratio variable as well as 3-day acute loads and 14-day chronic loads.

8.3.3 Multivariable analysis of previous established risk factors

In the case of sRPE, TD, and HSR, the greater the number of previous injuries a player had been exposed to in the preceding 12 month period, the higher the injury risk, while being exposed to no previous injuries was "*most likely*" beneficial to subsequent injury risk. The effect of match minutes changed substantially after adjusting for other risk factors. This meant that players experiencing low exposure to match minutes in the previous 12 month period were at a greater risk of subsequent injury, which was found to be the case in sRPE (1.27, 90% CIs:1.04-1.55, *likely harmful),* TD (1.36, 90% CIs:1.12-1.66, *very likely harmful*) and HSR (1.33, 90% CIs:1.09-

1.62, *likely harmful*). Players experiencing high exposure to match minutes experienced reduced risk; however, in the case of sRPE, TD and HSR these findings were only "*possibly harmful*". The effect of acute and chronic loads also changed dramatically after adjustment for other covariates. Examining the results of the multivariable analysis, in the case of sRPE and HSR based acute loads, the higher the acute load, the greater the relative risk of subsequent injury. In the case of TD, acute loads that were both higher and lower than the low moderate reference category (9-1042m) were at a substantially lower risk of injury. Examining the findings for chronic load, a range of results were apparent. High chronic workloads were demonstrated as being beneficial using the sRPE metric, harmful using the TD metric, and unclear using the HSR metric. The effect of low chronic loads were unclear across all three load measures.

Session Rating of Perceived Exertion					
		14	21	28	35
Rolling Averge	3	0.56	0.53	0.55	0.56
	5	0.54	0.51	0.53	0.53
	7	0.54	0.51	0.53	0.52
	9	0.53	0.49	0.52	0.52
Exponentially Weighted Moving Average	3	0.57	0.56	0.56	0.55
	5	0.56	0.55	0.55	0.54
	7	0.56	0.55	0.54	0.54
	9	0.55	0.55	0.54	0.53

Total Distance					
		14	21	28	35
Rolling Averge	3	0.52	0.52	0.52	0.49
	5	0.50	0.50	0.50	0.50
	7	0.52	0.51	0.52	0.51
	9	0.52	0.51	0.51	0.51
Exponentially Weighted Moving Average	3	0.57	0.57	0.56	0.56
	5	0.56	0.56	0.55	0.55
	7	0.56	0.56	0.54	0.54
	9	0.55	0.54	0.54	0.53

High Speed Running Distance					
		14	21	28	35
Rolling Averge	3	0.51	0.49	0.49	0.49
	5	0.49	0.50	0.51	0.49
	7	0.53	0.52	0.52	0.52
	9	0.53	0.53	0.51	0.50
Exponentially Weighted Moving Average	3	0.55	0.55	0.55	0.55
	5	0.55	0.54	0.54	0.54
	7	0.54	0.54	0.54	0.54
	9	0.54	0.54	0.54	0.53

Figure 8.1:Area under the curve (AUC) values for acute:chronic workload ratio values calculated using rolling averages and exponentially weighted averages, over different time periods (acute: 3, 5, 7, 9 days, chronic; 14, 21, 28, 35 days).

8.3.4 Acute:chronic workload ratio

Prior to any further analysis, correlation coefficients for the training load measures were calculated, with sRPE and TD variables demonstrating a large positive correlation ($r=0.69$, $p<0.01$) and sRPE and HSR variables showing a moderate positive correlation ($r=0.35$, $p<0.01$). In each analysis of the acute:chronic workload ratio and injury risk, covariates were included and adjusted for, with the included variables representing previous injury, match minutes, acute loads and chronic loads. Examining the relationship between the acute:chronic workload ratio and injury risk across three different load variables demonstrated a similar, although slightly different, relationship, with low values associated with the highest risk across sRPE, TD and HSR (Figure 8.2 and Table 8.2). For sRPE, a median acute:chronic value of 0.70 represented a daily injury hazard of 2.0% (90% CIs: 1.7-2.2). Compared to the median value for sRPE, values in the bottom percentiles as well as in the 25th percentile (0.15) represented "*most likely*" harmful hazard ratios of 3.5 (90% CIs: 2.9-4.3) and 2.6 (90% CIs: 2.1-3.1) respectively (Table 8.2). Values near the 75th percentile (1.21) represented "*most likely*" beneficial hazard ratio of 0.6 (90% CIs: 0.5-0.7). The resultant model was associated with an area under the curve (AUC) value of 0.76, with this AUC value representing the joint highest and, therefore, best performing model across each of the three load measures. A similar pattern existed in the TD GPS measure, with low values representing the highest risk and a "*most likely*" harmful effect (HR:2.1, 90% CIs: 1.5-2.9) (Figure 8.2 and Table 8.2). A "*very likely*" harmful effect of being in the 25th percentile was observed (HR:1.7, 90% CIs: 1.3-2.4), compared to a mean injury hazard of 1.5%, with athletes near to the 75th percentile (1.25) being at lower risk, although these effects were only "*possibly*" clear (HR:0.8, 90% CIs: 0.6-1.1). The resultant model was associated with an AUC value of 0.76, which also represented the joint highest performing model based on AUC score. Finally, when looking at the HSR GPS variable, a slightly different pattern emerged to that of sRPE and TD. Although lower values of the acute:chronic workload ratio were associated with the highest risk, none were seen to produce clear results. It was, however, found that high acute:chronic values were associated with a clear "*most likely*" beneficial effect observed (HR:0.3, 90% CIs: 0.1-0.5). The resultant model was associated with an AUC value of 0.74, with this value representing the poorest performing model across each of the 3 load measures used. In the final analysis undertaken, where acute:chronic values of GPS metrics were included and adjusted for in a model alongside sRPE as the variable of interest, sRPE derived acute:chronic values demonstrated a similar pattern of injury risk to that of sRPE and TD alone, with a U-shaped curve representing injury risk for a player (Figure 8.2D). Given this, acute:chronic workload values in the lowest quintiles of sRPE represented "*most likely*" harmful effects on injury risk (HR: 3.2, 90% CIs: 2.5-4.1 and HR: 2.4, 90% CIs: 1.8-3.1 respectively: Table 8.2). Values representing the 75th percentile (acute:chronic of 1.21) represented a "*very likely*" beneficial effect on injury risk (HR: 0.6, 90%

CIs: 0.4-0.9) and finally at the upper end of the acute:chronic scale a *"likely"* harmful effect was evident (HR: 1.4 90% CIs: 1.0-2.0). The resultant model was associated with an AUC value of 0.76, which suggests no added benefit of GPS measures compared to sRPE alone.

Analysis of the acute:chronic workload ratio calculated over the time period 7 and 28 days (typically used in previous research), outlined a similar profile of risk for players with clear harmful changes in risk at the lower end of the acute:chronic workload ratio (Appendix G). A value in the 75th percentile of acute:chronic values also represented a "*likely"* beneficial effect on injury risk (HR: 0.8, 90% CIs: 0.7-0.9: Appendix G).

Table 8.1: Analysis of previously documented injury risk factors, in a univariate manner (Column 5) as well as after adjustment for other risk factors (Column 6). Likelihood of increased risk of injuries: * possibly, ** likely, ***very likely, ****most likely. Arrows indicate increase or decrease in relative risk after adjustment for other covariates

Load Variable	Covariates	Category	Unit	Relative Risk (90% CIs)	New Relative Risk (after adjustment for other covariates)
sRPE	Previous Injury	Low	0	0.01 (0.001- 0.03)****	0.01 (0.001-0.03)****
		Mod Low	1	1.0	1.0
		Mod High	2	1.41 (1.15-1.72)***	1.45 (1.18-1.79)*** ↑
		High	4-15	3.20 (2.69-3.80)****	3.43 (2.84-4.15)**** ↑
	Match Minutes	Low	0-296	0.74 (0.61-0.89)***	1.27 (1.04-1.55)** ↑
		Mod Low	297-665 (Ref)	1.0	1.0
		Mod High	666-1172	1.10 (0.93-1.31)	0.86 (0.73-1.02)* ↓
		High	1173-2452	1.18 (0.97-1.42)	0.88 (0.74-1.05)* ↓
	Acute Load (AU)	Low	0-2	1.82 (1.40-2.38)****	0.58 (0.38- 0.88)*** ↓
		Mod Low	3-104	1.0	1.0
		Mod High	105-293	0.45 (0.38-0.54)****	1.06 (0.81-1.37) ↑
		High	294-1872	0.40 (0.34-0.47)****	1.78 (1.26-2.53)**** ↑
	Chronic Load (AU)	Low	0-40	1.64 (1.30-2.07) ****	0.83 (0.58-1.18) ↓
		Mod Low	41-145	1.0	1.0
		Mod High	145-301	0.82 (0.71-0.95) **	0.95 (0.78-1.15) ↑
		High	302-1216	0.50 (0.42-0.60) ****	0.68 (0.61-0.89) *** ↑
GPS (TD)	Previous Injury	Low	0	0.01 (0.001- 0.03)****	0.01 (0.001-0.03)****
		Mod Low	1	1.0	1.0
		Mod High	2	1.41 (1.15-1.72)***	1.48 (1.20-1.82)*** ↑
		High	4-15	3.20 (2.69-3.80)****	3.53 (2.92-4.27)**** ↑
	Match Minutes	Low	0-296	0.74 (0.61-0.89)***	1.36 (1.12-1.66)*** ↑
		Mod Low	297-665 (Ref)	1.0	1.0
		Mod High	666-1172	1.10 (0.93-1.31)	0.88 (0.74-1.04)* ↓
		High	1173-2452	1.18 (0.97-1.42)	0.89 (0.74-1.05)* ↓
	Acute Load (Metres)	Low	0-8	0.78 (0.61-0.99)**	0.49 (0.31-0.78)*** ↓
		Mod Low	9-1042	1.0	1.0
		Mod High	1043-2268	0.51 (0.42-0.60)****	0.61 (0.47-0.79)**** ↑
		High	2688-14588	0.51 (0.43-0.59)****	0.57 (0.40-0.80)*** ↑
	Chronic Load (Metres)	Low	0-357	1.65 (1.30-2.09)****	1.01 (0.67-1.53) ↓
		Mod Low	358-1378	1.0	1.0
		Mod High	1379-2116	1.28 (1.08-1.52)**	1.65 (1.36-2.02)**** ↑
		High	2117-7091	1.46 (1.23-1.73)***	2.52 (1.98-3.22)**** ↑
GPS (HSR)	Previous Injury	Low	0	0.01 (0.001- 0.03)****	0.01 (0.001-0.03)****
		Mod Low	1	1.0	1.0
		Mod High	2	1.41 (1.15-1.72)***	1.47 (1.19-1.81)*** ↑
		High	4-15	3.20 (2.69-3.80)****	3.39 (2.82-4.09)**** ↑
	Match Minutes	Low	0-296	0.74 (0.61-0.89)***	1.33(1.09-1.62)** ↑
		Mod Low	297-665 (Ref)	1.0	1.0
		Mod High	666-1172	1.10 (0.93-1.31)	0.88 (0.75-1.04)* ↓
		High	1173-2452	1.18 (0.97-1.42)	0.93 (0.78-1.10)* ↓
	Acute Load (Metres)	Low	0-2	1.03 (0.81-1.30)	0.61 (0.41-0.90)** ↓
		Mod Low	2-41	1.0	1.0
		Mod High	42-139	0.85 (0.72-1.01)*	1.08 (0.85-1.38) ↑
		High	140-2322	0.76 (0.64-0.90)**	1.22 (0.87-1.71) ↑
	Chronic Load (Metres)	Low	0-14	1.22 (0.98-1.52)**	1.13 (0.80-1.59) ↓
		Mod Low	15-65	1.0	1.0
		Mod High	66-150	1.10 (0.94-1.29)*	0.98 (0.81-1.19) ↓
		High	151-1486	1.04 (0.87-1.24)	1.00 (0.77-1.31) ↓

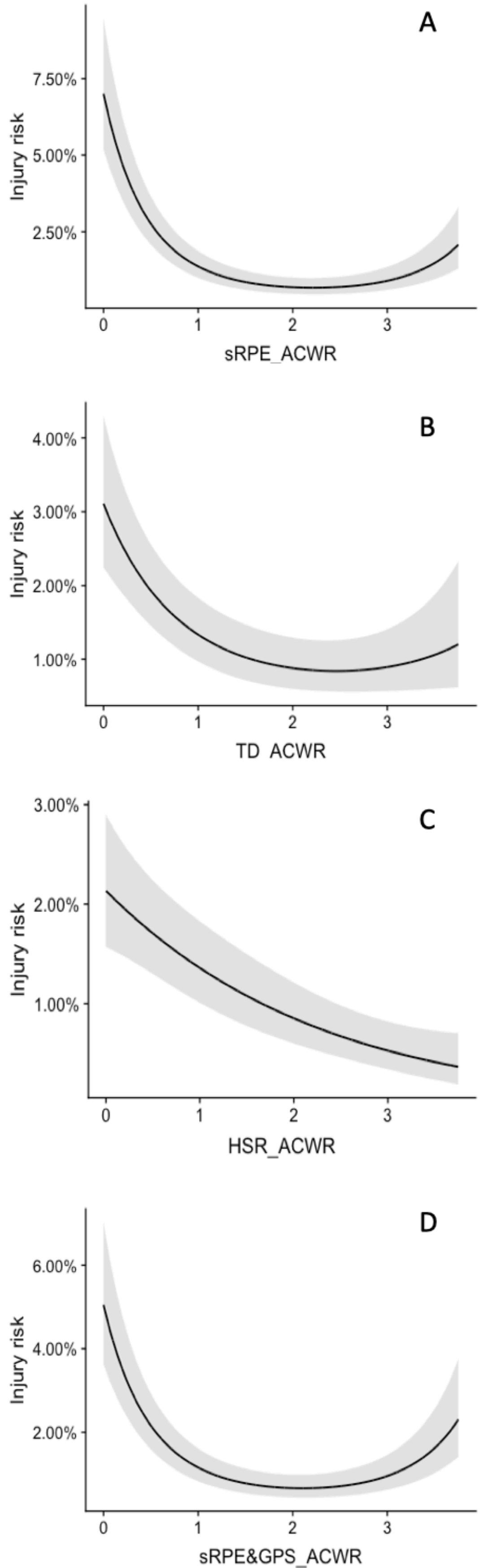

Figure 8.2: Relationship between Injury risk (Y-axis) and acute:chronic workload ratio (ACWR) (X-axis). Injury risk represented by injury hazard: risk per player per exposure day. A: sRPE, B:TD, C: HSR, D: sRPE adjusted for TD and HSR acute:chronic values.

Table 8.2: Main effect of different acute:chronic workload ratio (ACWR) values on injury risk. Injury Hazard represents risk of injury per player per exposure day. Likelihood of change in risk of injuries: * possibly, ** likely, ***very likely, ****most likely. AUC: Area under the curve.

Training Load measure	Training Load Metric	Quartile	ACWR Value	Injury Hazard % (90% CIs)	Hazard Ratio (90% CIs)	Model AUC
sRPE	sRPE ACWR	0	0	7.0 (5.4-7.3)	3.5 (2.9-4.3)****	0.76
		0.25	0.15	5.1 (4.1-5.4)	2.6 (2.1-3.1) ****	
		Median (Ref)	0.70	2.0 (1.7-2.2)	1.0	
		0.75	1.21	1.1 (1.0-1.3)	0.6 (0.5-0.7) ****	
		1	3.75	2.1 (1.7-2.8)	1.1 (0.8-1.4)	
GPS (TD)	TD ACWR	0	0	3.1 (2.0-3.5)	2.1 (1.5-2.9) ****	0.76
		0.25	0.19	2.6 (1.8-2.9)	1.7 (1.3-2.4)***	
		Median (Ref)	0.79	1.5 (1.2-1.8)	1.0	
		0.75	1.25	1.2 (0.9-1.4)	0.8 (0.6-1.1)*	
		1	3.75	1.2 (0.7-1.9)	0.8 (0.5-1.4)	
GPS (HSR)	HSR ACWR	0	0	2.1 (1.6-2.8)	1.4 (1.0-2.0)	0.74
		0.25	0.14	1.9 (1.5-2.3)	1.3 (0.9-1.8)*	
		Median (Ref)	0.67	1.5 (1.1-1.8)	1.0	
		0.75	1.18	1.2 (0.8-1.6)	0.8 (0.5-1.2)	
		1	3.75	0.4 (0.2-0.6)	0.3 (0.1-0.5)****	
sRPE & GPS (TD and HSR)	sRPE ACWR (adjusted for TD and HSR ACWR)	0	0	5.1 (3.9-5.6)	3.2 (2.5-4.1) ****	0.76
		0.25	0.15	3.8 (3.0-4.2)	2.4 (1.8-3.1) ****	
		Median (Ref)	0.70	1.6 (1.3-1.9)	1.0	
		0.75	1.21	1.0 (0.7-1.3)	0.6 (0.4-0.9)***	
		1	3.75	2.3 (2.1-3.7)	1.4 (1.0-2.0)**	

8.4 Discussion:

This was a large study of six professional rugby union teams over a one-season period, with 363 participants included in the final dataset for whom 885 injuries were recorded. The aim of this study was to identify whether a link between training load and injury risk existed and whether internal or external load metrics produced similar outcomes. When using sRPE and two GPS metrics (TD and HSR) a similar pattern of risk was apparent with low acute:chronic values associated with the highest risk of injury. Based on the AUC scores, sRPE and TD provided the best performing model of injury risk, with an AUC of 0.76. Models including both measures of sRPE and GPS, demonstrated similar risk profiles to that of sRPE or TD measures in isolation, highlighting clear harmful effects at either end of the acute:chronic workload ratio scale. The AUC value for this model, with both measures of sRPE and GPS, reported an AUC of 0.76, equalling that of either in isolation, suggesting limited additional benefit when using the two measures together. The results of this study indicate that current median values experienced in this setting, using an exponentially weighted 3 to 14 day acute:chronic workload ratio, are not optimal for minimising injury risk and, therefore, conditioning staff should aim to ensure that players training load scores are closer to that currently seen as the 75th percentile for each respective load metric.

In Chapter Six of this thesis, clear associations were demonstrated within a large rugby union cohort using just the sRPE measure of training load. Given the relative value paced on GPS measures by practitioners within rugby union (Chapter Seven), this study aimed to identify whether similar associations between training load and injury existed using the same measures but also with GPS measures and whether a combination of measures might provide more insight. Of the two GPS measures included [total distance (TD) and high speed running (HSR)], the TD metric was deemed to represent a higher performing tool for detecting changes in injury risk using the AUC score as the criterion measure (0.76). The relationship between the acute:chronic workload ratio and injury risk when using TD as the variable of interest demonstrated a U-Shaped curve, similar to that for sRPE in Chapter Six. This finding not only represents a "*most likely*" harmful effect on injury associated at the lower end of the acute:chronic workload ratio scale, but also represent a "*possibly*" beneficial effect of values close to 1.25. Using TD as the load measure of interest closely mirrored the findings associated with the sRPE measure. This finding may not be surprising given the previous evidence that a correlation exists between sRPE and TD GPS measures (Lovell et al., 2013), with correlations ranging from 0.37 to 0.88 depending on the session type. Although not split by session type in this study, the overall correlation between the sRPE and TD measures was 0.69 which is considered a moderate strength correlation. High speed running distance was the poorest performing of the three measures used to assess injury risk; however, no substantial difference existed in the AUC values representing the models (0.74 for HSR model). Different to that of both TD and sRPE measure however was that as the HSR acute:chronic workload ratio value got higher, the risk of injury was lower with "*most likely*" beneficial effects associated with high acute:chronic values. Unlike TD and sRPE, at lower acute:chronic values, only unclear effects were evident.

When using the sRPE measure in isolation, a clear association between load and injury is evident with a "likely harmful" effect associated with low acute:chronic workload values. This offers further support for the use of the acute:chronic workload ratio in the context of rugby union when using the internal load measure, sRPE. The AUC value for the sRPE model was the joint highest across all three of the measures collected (0.76), supporting the theory that the internal load is the most important factor in determining training outcome (Impellizzeri et al., 2019a), while it also supports the call for the use of sRPE in monitoring programmes, not only in rugby union (Quarrie et al., 2016) but across sports (Eckard et al., 2018). Comparing 3 to 14 day acute:chronic periods with the more typically used 7 to 28 day acute:chronic periods resulted in similar findings, providing evidence for the importance of these low acute:chronic workload ratios, and indicating this is not an artefact of the 3 to 14 day calculation method. Overall therefore, the acute:chronic workload ratio (derived from the sRPE measure) is a useful measure for managing injury risk, through modification of athlete workload to avoid low acute:chronic values.

To identify whether the inclusion of GPS data within the injury risk models provided any further information over and above that which is provided by sRPE alone, both the TD and HSR were added to the sRPE model. This data was entered in the form of acute:chronic workload ratio and held at values representing the 75th percentile (low risk) for the results presented in Table 8.2. It has previously been outlined that, while useful, external load measures such as GPS can be limited in that the response of two athletes to the same external load may be different, and, therefore, it is suggested that internal load represents a better measure of the functional outcome of training (Impellizzeri et al., 2019a). The findings of the analysis within this chapter would suggest that the inclusion of both internal and external loads adds little value beyond that of sRPE or TD alone, although it does offer greater utility than that of HSR in isolation. What was evident, however, was that when GPS measures were included in the model, the values associated with the upper end of the acute:chronic scale were clearly harmful, supporting the risk profile including a sweet spot as proposed by Gabbett, (2016a). This finding suggests that the inclusion of GPS metrics within a model including sRPE may provide more sensitive measures at the upper end of the acute:chronic value scale. Given the expense, time and effort in capturing GPS data, it appears that when this data is added in the form of an acute:chronic workload ratio, little value is added. For this reason, when managing injury risk in rugby union, the sRPE measure alone is useful without the inclusion of GPS. However, should GPS data be used for driving external load prescription, managing specific injury risk type or assisting in the return to play process, the utility of these metrics is still of great value to the club. Adjusting for GPS metrics within a model by using acute:chronic workload ratios derived from those metrics was the approach used within this study. That being stated, the way in which these GPS variables are included in future investigations may influence the performance of the model, with acute or chronic GPS loads in isolation potentially providing more useful additions than that of an acute:chronic workload ratio. For example, studies such as that by Malone et al. (2017c) investigating the effect of low and high chronic loads on an athlete's capacity for covering distance at maximal velocity may be an avenue for further exploration; however, are yet to be conducted within this cohort. Within the current cohort, undertaking investigations of this type would be desirable; however, there are several possible combinations of metrics for inclusion in the analysis (e.g. HSR low acute, high acute, HSR, low chronic, high chronic etc). To avoid inflating Type I error rate through multiple comparisons, these investigation were not included in the present study but further consultation with stakeholders could drive specific research questions that need addressing. Until such time when evidence to this effect has been investigated, this study suggests that the addition of GPS measures to sRPE does not improve the ability of the model to detect changes in injury risk; however, the utility of TD measures in isolation proved to be of similar value to that of sRPE alone.

The one finding which was shared by all three variables and their respective associations with injury risk was that acute:chronic values that were greater than the currently observed median values represented a lower risk. This was the case with all three variables, with the effects seen as "*most likely*", "*possibly*" and "*most likely*" beneficial for the sRPE, TD and HSR variables, respectively. In previous work, the existence of a "sweet spot" has been documented and although different exact sweet spot values have been reported, the data represented as low risk in the current study for sRPE and TD variables sits within the commonly used value of 0.8-1.3 (Gabbett, 2016a). For HSR, although an acute:chronic value within this previously documented sweet spot does offer a hazard ratio of 0.8, this finding was unclear, with a higher acute:chronic value representing an even lower risk. Across all three variables, what is clear is that the median acute:chronic value does not represent the lowest possible risk for players and is, therefore, not optimal for minimising injury risk. As discussed in Chapter Six, the reasons why a lower acute:chronic value is of greater risk than that of a higher value requires further investigation. In previous literature, low loads have also been shown to potentially leave athletes unprepared for the demands of their respective sports, but it has predominantly been spikes in the acute:chronic workload ratio that have been reported as being of greater risk to athletes (Drew and Finch, 2016; Gabbett, 2016b). The repetition of these findings showing a link to low acute:chronic values and injury risk (not only across multiple load variables but also across different data collections) would suggest that the three day period in the build-up to a fixture, for example, is an important period and undertaking further work to understand how best to structure training in this period is needed. From the perspective of injuries occurring in training, the importance of a regular training stimulus being provided to athletes to minimise injury risk is clear.

Similar to the work undertaken in Chapter Five, an exponentially weighted average calculated over 3 (acute) to 14 (chronic) day periods represented the calculation method deemed most appropriate for managing injury risk. This was not only the case for the sRPE measure but was also seen using the two GPS metrics. Comparison of AUC and AIC values displayed contrasting values as to which method was the most appropriate for acute:chronic workload calculation. Given this, the AUC measure was chosen as the measure to use for method selection given its use in previous studies (Colby et al., 2017). Although not a primary aim of the current study, four other risk factors were examined for their relationship with injury risk, namely: previous injury and match injury (both in the past 12 months) as well as acute and chronic workloads in isolation. This analysis demonstrated that a greater number of previous injuries represented a higher risk of subsequent injury, with no previous injury being "*most likely*" beneficial to injury risk. The pool of players in the upper category, with 4-15 previous injuries in the preceding 12 months is likely to represent a pool of players who may be considered to be in a continuous cycle of rehabilitation, as outlined by Gabbett (2016a). Athletes playing a low number of match minutes in the preceding 12 months were also shown to have a higher risk than those with a "low moderate" exposure, while those with high match minutes exposure demonstrated possibly beneficial effects. These findings are different to those of Williams et al., (2017c) who demonstrated an increase in risk with high match minute categories. Since the publication of this study, it is possible that there is a greater awareness of the increased risk associated with high match exposure and, therefore, an improved management of player match loads. The current limit on full match equivalent exposure in professional rugby union in England is 30. In the present study, match minutes ranged from 7 to 2191 (27 full match equivalents) demonstrating adherence with the match exposure guidelines. Further to this, only 44 players surpassed 20 full game equivalents, with only 8 playing more than 25. This may mean that increased awareness around playing volumes have had a positive impact with the current moderate high to high exposure in this study being in the safe zone outlined by Williams et al., (2017c) of 15-35 fixtures. Players experiencing higher injury rates in the lower match minute categories, this may represent a constant 'rehab-er' cohort; players who break down repeatedly due to their recent previous injury history, and their training loads being insufficient to adapt to match demands (Gabbett, 2016a). The findings related to acute and chronic loads in isolation were contrasting depending on the variable used, with high acute loads associated with a greater risk in sRPE and HSR variables, but not in TD, while high chronic loads were seen to be beneficial (sRPE), harmful (TD) and unclear (HSR). A number of reasons for these findings are possible and given that these were not the primary aims of the study, further exploration is required.

While every step was taken to try and minimise the limitations with this study, there are a number which must be addressed. The purpose of Chapter Seven was to establish a group of teams who used similar GPS units and collected data using comparable methods. While the majority of previous studies of this type have used one team samples meaning GPS data is collected in the same manner for the study period, it was hoped that using multiple teams might provide more generalisable information to practitioners as the findings would not be specific to one team and the way in which their sports medicine team works. Despite best efforts and although all units were from the same GPS unit provider, differences existed in the actual collection units and software versions used. Another limitation associated with the collection across multiple clubs was the use of multiple definitions for high speed running. As this was an observational study, clubs were asked to continue using the structures already in place to avoid any extra burden of data collection. This did, however, lead to differences between clubs with both relative and absolute values used. For these reasons the findings associated with HSR and a very high ACWR associated with a "*most likely*" beneficial effect on injury risk may be affected and should be interpreted with caution. Despite these differences in collection methods, a recent study demonstrated that, when standardised, no meaningful difference existed between absolute and relative speed thresholds (Thornton, Delaney, Bartlett and Duthie, 2019). While the standardisation process involved in the work of Thornton et al., (2019) was different to that of an acute:chronic workload ratio, the findings indicate that standardisation processes may offer the ability to compare GPS data collected through different means, yet this is still to be investigated in the context of the acute:chronic workload ratio. What this dataset does offer, however, is an opportunity to compare the relationship between training load and injury risk using different definitions of HSR. Future work exploring GPS data across multiple clubs may also wish to consider the collection of raw GPS data so standardised measures can be calculated and used by the research team. The aim of this work was to compare GPS based metrics to that of sRPE; however, it must be considered that the role of running based metrics may not have the greatest influence over injury risk in rugby union, with contact likely to be of greater importance. Further exploration of contact based load, whether derived through accurate GPS based metrics or counts derived from video analysis may offer further valuable insight into injury risk in rugby union. One further area of potential exploration may be in picking apart the exact structure of weekly training and the periods directly before the onset of an injury. Although all load was considered the same within this study from an sRPE perspective, dividing this out based on the training type may offer more insight into the reasons for the increase in injury risk associated with low acute:chronic workload values.

This study has outlined the relationship between training load and injury risk across multiple training load metrics. Despite the increased value placed on GPS derived metrics, it would appear that sRPE provides a similar performance as an indicator of injury risk compared to the two variables examined within this study, TD and HSR, which are widely used and valued in rugby union. Further to this, the shape of the curve representing the load-injury relationship is similar across sRPE, TD, and sRPE and GPS measures combined. Further to this, the inclusion of GPS and sRPE derived acute:chronic workload ratio values within the same model does not improve the sensitivity of the model over and above the use of either metric in isolation. In conclusion, these findings outline the high risk of injury associated with low acute:chronic workload ratios and, therefore, it is recommended that conditioning staff strive to maintain steady and regular training exposures for athletes to minimise the risk of injury.

CHAPTER 9

General Discussion

9.1 Introduction

This thesis aimed to investigate the relationship between training load and injury risk in a large sample of professional rugby union players. Chapter One outlined the main research questions with a number of aspects of training load and injury risk addressed, including historic trends, methodological considerations, the moderating effect of other risk factors, and different load measurement types. Chapter Two reviewed the existing literature pertaining to training load and injury risk in the context of all sport and in particular, professional rugby union. Chapters Three to Eight addressed the research questions using population level data, team level data and individual player level data. The present Chapter aims to synthesise the keys elements of this thesis and to critically assess the implications of these findings for future practice and research, while also suggesting avenues for further progress in this rapidly evolving field.

9.2 Addressing the Research Questions

9.2.1 Have training volumes and training injury risk changed over time in professional rugby union?

In Chapter Three it was shown that over an 11-season period, training volume per player remained stable with players completing 6 hrs 48 mins of training per week (95% CIs: 6 hrs 30 mins - 7 hrs 6 mins) on average. While the incidence of training related injuries remained stable (incidence rate: 2.6/1000 player-hours, 95% CI: 2.4 - 2.8), the mean severity (days lost) rose from 17 days per injury to 37 days on average. Full contact training represented the highest incidence of injury and non-gym-based conditioning represented the highest severity of injury.

Although this team-level data provides useful insight into the temporal trends of training volume and injury, training volume quantified as hours per player per week is limited as it does not take into account training intensity. Given this, it is not possible to establish whether the relative intensity of training has remained stable or has increased, which may explain the rise in both injury severity and burden. To build upon this, and to measure both intensity and duration, the session Rating of Perceived Exertion (sRPE) method was chosen as the main training load measure for the remaining work of the PhD thesis.

9.2.2 Are there associations between training load, injury burden and performance in rugby union at a team average level?

For Chapter Four, the sRPE measure was captured across 13 clubs over a 2-season period. Using this data, it was shown that an association between training load and injury risk existed, with high team-average derived acute:chronic workload ratios associated with a "*possibly*" harmful change in injury risk. High injury burden was associated with a "*likely*" harmful effect on team performance with this being demonstrated on a weekly basis, compared with previous studies of season-long team performance. While team performance appeared not to be clearly associated with team average training load metrics, the link between injury burden and performance demonstrate the value in managing training load appropriately to minimise injury risk and, therefore, aid performance.

The findings of Chapter Four demonstrated the benefits of managing player load to minimise injury risk and, therefore, supported the investigation of changes in training load measures on injury risk using individual level data.

9.2.3 What are the best methods when using session Rating of Perceived Exertion (sRPE) data to inform practitioners on injury risk management in rugby union? The three methods specifically targeted, which concern the calculation of an acute: chronic workload ratio are:

a. Exponentially weighted moving averages versus rolling averages
b. Acute and chronic time windows used
c. Coupled or uncoupled ratios

In Chapter Five, using individual data from the 13 clubs over two seasons, an assessment of data aggregation and calculation methods was undertaken to optimise the potential utility of the data used in this investigation. This chapter identified that the typically used 7:28 days acute:chronic workload ratio adopted widely in practice may not be appropriate in this setting. While some variation existed between teams as to the best methods for calculating these training variables, some common themes emerged across multiple clubs. Across each team individually as well as when data was pooled together, these analyses identified coupled loads, exponentially weighted averages, 3-day acute periods, and 14-day chronic periods as the best-fitting parameters of the acute:chronic workload ratio. The acute:chronic workload ratio that demonstrated the most support across clubs, as well as when the data was pooled, was that of a 3:14 day exponentially weighted and coupled load.

9.2.4 What is the relationship between sRPE derived training load and risk of injury in professional rugby union?

Having selected the most appropriate of the sampled training load measurements in Chapter Five, in Chapter Six the association between training load and injury risk was investigated across 13 clubs over a two season period. This was undertaken while also accounting for other previously documented risk factors including previous injury, previous concussion and cumulative match minutes in the preceding 12 months. While a U-shaped curve in injury risk was evident based on acute:chronic workload values, the highest risk of injury was evident when the acute:chronic workload ratio was low, with "*most likely*" and "*very likely*" harmful effects. This relationship was consistent for both non-contact soft tissue injuries alone and all injury types. This study is, therefore, the first to demonstrate a clear link between acute:chronic workloads and injury risk in rugby union.

9.2.5 What is the value placed on monitoring variables by clubs when making decisions on injury risk and player performance, and are the methods by which these variables are collected common across all clubs?

To explore the feasibility of conducting a multi-club study capturing sRPE and Global Positioning Systems (GPS) data, in Chapter Seven a questionnaire that was completed by practitioners from each team within the English Premiership. There was wide variation in responses, as the value placed on different monitoring metrics was specific to each individual club. GPS was regarded as more important than sRPE for managing injury risk and assessing player performance. This study also demonstrated the widespread heterogeneity of data collection methods utilised for capturing metrics that were thought to represent the same value in players, for example, high speed running. Using the responses from this study, a sample of six teams was identified to participate in a study investigating training load and injury risk, in which both measures of internal (sRPE) and external load (GPS) would be used.

9.2.6 Does the addition of external load measurement tools [in the form of Global Positioning Systems (GPS) data] provide additional insight, over and above sRPE, on the relationship between training load and injury risk in professional rugby union?

In Chapter Eight, sRPE and total distance and high speed running from GPS were assessed for their relationships with injury risk in this 6 team, single-season study. Similar calculation methods to those used in Chapter Five were identified as performing well for all three measures, using 3 to 14 day exponentially weighted acute:chronic workload values. A similar pattern of injury risk was evident, with both low and high acute:chronic values representing harmful changes in injury risk, compared with values around 1.25. Both sRPE and total distance measures performed well in modelling injury risk, with AUC values of 0.76. High speed running also performed well (AUC: 0.74) but demonstrated a negative linear relationship with injury risk. This finding, however, may be limited due to the large differences in recording methods across clubs for the HSR variable. A model including acute:chronic workload ratio values for both sRPE and GPS measures suggested that the addition of both internal and external measures to the modelling process was no better at detecting changes in injury risk than that of sRPE or TD measures alone (AUC: 0.76). However, this model may add more sensitivity at the upper values of the acute:chronic workload ratio, with clearly harmful changes in risk reported. This chapter, alongside Chapter Six, demonstrated the clear associations between training load and injury risk in rugby union.

9.3 Original contribution to the literature

While the field of training load is one that is rapidly evolving and constantly being improved through study design, technology advancements and statistical advancements, this PhD thesis has made an original and meaningful contribution to the current literature through:

- Completing a longitudinal analysis of trends in training volume in rugby union, alongside an assessment of injury patterns.
- Providing the first study in rugby union to examine the relationship between training load, injury risk and performance, with the majority of previous research examining only two of these three components.
- Providing the first study to examine multiple calculation methods outlined in the current literature for producing acute:chronic workload ratios and demonstrating the potential utility of club-by-club calculation methods compared with a ‘one size fits all’ approach.
- Undertaking the largest training load and injury risk data collection recorded across all sport, with data gathered from 696 professional rugby union players and including over 1700 injuries.
- Documenting for the first time a clear association between the acute:chronic workload ratio and injury risk in rugby union, using sRPE.
- Reinforcing previous evidence supporting the use of multivariable analysis when analysing risk factors for injury.
- Outlining substantial differences in relative value, methods used and capture practices of professional clubs for athlete monitoring, calling for more collaboration between clubs to achieve consensus to enhance athlete welfare in the sport.
- Demonstrating the utility of sRPE as a simple and cheap load measurement tool, which appears to be just as effective as GPS for modelling injury risk in rugby union

Taking all of these points into account, this body of work represents the most complete investigation into training in elite rugby union. From outlining historic trends in training and injury data to analysing multiple measurement tools for their association with injury, this thesis outlines several key messages to coaches regarding how training may influence injury risk. While not only providing insight into the most high-risk scenarios for injury risk, the thesis also explores a number of other risk factors for injury. While focusing largely on injury risk as the outcome measure, this thesis also attempts to contextualise these findings in the wider sporting arena, considering the potential subsequent effects on team performance.

9.4 Practical implications and impact

This thesis aimed to address a problem of great importance to modern day practitioners working within sports. However, training load and injury risk is a growing research field, with a substantial number of recent publications across multiple sports. It is for this reason that the implications and impact of this work have been divided into two sections, focusing on practical implications for both research and practice.

9.4.1 For Research

The majority of research on training load and injury risk to date comes from sources of data embedded within monitoring practices of professional sports clubs. This research is, therefore, driven by questions specific to that team or sport, conducted with a convenience sample and often limited to a single team over one or two seasons, with a low number of participants (median of 46) (Windt et al., 2018). While valuable, the generalisability of these results is limited given the widespread differences in monitoring practices identified in Chapter Seven. This thesis aimed to work closely with each of the clubs across the English Premiership to capture training load from a large sample of players, to improve the generalisability of the findings and to increase statistical power to confidently report findings. Studies such as these are rare due to the complexity of their organisation, yet have been called for within the current literature, specifically in rugby union (Quarrie et al., 2016).

Having a large sample may be useful for improving generalisability, strengthening statistical power and reducing the risk of overall error in results (Carey et al., 2018), but the organisation and operational procedure involved in such studies are difficult. The main challenges experienced within this thesis concerned data collection methods and quality. As demonstrated in Chapter Seven, the way in which data was collected, stored and used across clubs varied for GPS and pilot work for Chapters Four and Five indicated similar issues for sRPE measures. This meant that bespoke data capture forms were offered to each club, should they not have suitable alternatives in place. Further to this, a number of mechanisms were in place to ensure data quality throughout the study. As part of the competition agreement for participating in the top tier of English rugby union, all clubs must provide injury data using an online capture platform as outlined in each

Chapter. Injury surveillance across the league has been ongoing since 2002 and is extensively evaluated, with quality improvement completed at regular intervals, including the move to online data capture in the 2011-12 and the introduction of an injury validation mechanism for match injuries in the 2016-17 season. With regards to training load data, Chapter Seven observed that the training load data captured by clubs is used daily to inform injury risk management and performance assessment decisions. Given the importance of the data in making these decisions, it is, therefore, assumed by the practitioner and researcher, that the quality of the data produced by monitoring tools is of high enough quality to be assistive in decision making. The impact of this study, as future guidance for others trying to undertake such research using a similar design, is to ensure a balance is struck between a large sample size and a well-structured and rigorous data collection process assessing a number of key metrics.

When undertaking a multi-club study where numerous predictor and outcome variables are being collected simultaneously, a number of important considerations for research design and smooth operation of the project are needed. Large-scale injury surveillance studies are now commonplace across many of the major sporting leagues in the world, however, validation of the data being input into these systems is a challenge (Ekegren et al., 2016). Despite the difficulties involved, over the course of this study, a method for validation of match injury has been developed and integrated into weekly practice for the project. While this involves greater time input from the researcher, ensuring the validity of the data is essential and, therefore, future work in this area should consider employing a mechanism for validation within the operation of any such work. Further to this, a number of system considerations are required to minimise the effort required by clubs and staff to input data while maximising the output for those using the data. It is, therefore, recommended that researchers (working with online platforms) work closely with the developers of the data capture platforms, to review data capture procedures, put in place operational manuals for inputting data and to facilitate transition periods for new staff members or system updates. Given the sensitivity of the data being collected, especially in the case of private medical data, ensuring the necessary protection of data is in place is also imperative. While these tasks are somewhat context specific, the role of any researcher in a large-scale study such as this is to facilitate the needs of the medics and conditioning staff within the clubs logging the data on a daily basis. Central to this role is maintaining good communication lines with the practitioners to ensure club buy-in is maintained, while also engaging them in the process as much as possible. This relationship is essential to the success of these project types and may be assisted with feedback to clubs through bespoke reports, assistance with club monitoring (for example, data collection spreadsheets) or in the engagement of staff in formulating research questions specific to them or the sport as a whole.

9.4.2 For Practice

This thesis aimed to answer questions about minimising injury risk so the management of athletes in rugby union could be improved. Although a number of key results are outlined within the Chapters themselves, in this section the focus will be on the implications of load management for daily athlete monitoring.

9.4.2.1 Is the acute:chronic workload ratio worth the effort?

In previous literature, as well as the current thesis, the acute:chronic workload ratio has clearly been associated with injury risk (Chapters Four, Six, Eight). Yet, contradictory findings are evident depending on the methods used. For example, team average data suggests that high acute:chronic values are associated with injury risk (Chapter Four), but with individual level data, a higher injury risk was associated with low acute:chronic values (Chapters Six and Eight). Importantly, when looking at any measure of load, such as the acute:chronic workload ratio, the measure should not be evaluated in isolation as it does not represent the only factor influencing injury risk (Windt et al., 2017; Gabbett, 2018). Not only is it the case that other risk factors may influence injury risk, but it is also likely that these relationships and injury risk profiles will be specific to each individual athlete (Meeuwisse et al., 2007; Warren, Williams, McGraig and Trewartha, 2018). Therefore, in studies of the acute:chronic workload ratio where positive associations are found, the exact nature of the relationship will likely be specific to each individual, with unique risk thresholds based on individual risk factors. It is, therefore, recommended that, should a practitioner wish to use the tool in the management of their athletes, a regular review of acute:chronic thresholds is conducted to establish changing risk profiles based on ever evolving risk factors. Given the fast-paced and often frantic structure of high-performance sport, reviews of this type may be possible only once per season as part of an annual review; however, this may provide useful information to coaching staff about the relative importance of specific metrics as well as the changes in baseline risk characteristics for each player. For example, should a player experience one new injury and get an extended period of match exposure, the risk factors for that player have now changed and, therefore, the thresholds for training load measures may have shifted to represent these changes.

In general, whether it is the acute:chronic workload ratio that is utilised by coaching staff or whether it is other specific load metrics, the selection of training load measures is entirely the choice of the team overseeing the players. How they use this information in their daily practice is also likely to be unique to each club. However, the information their chosen measurements actually provide is not well understood and this creates a fundamental problem when it comes to athlete management. The premise of a workload measurement tool is that it provides feedback on the fitness and fatigue state of an athlete at any given time (Gabbett, 2016a). However, these assessments have traditionally been the domain of coaching, where skilled practitioners are able to periodise training and identify the individual needs of their athletes. Therefore, the use of workload measurement tools becomes a method of confirming what coaches already observe and act upon as a matter of routine. Although coaches have been using intuition to manage athletes, since well before the introduction of formal load monitoring, with the increase in data in modern sport, there appears to have been a shift away from this intuitive process, with coaches relinquishing this role in favour of relying on data. The appropriate use of data to inform decision making, while favourable, does still rely on the context from the coach, which suggests the shift towards a reliance on data still requires the intuition of a coach to make appropriate decisions. While different philosophies are apparent in the way clubs use load monitoring tools, two key considerations remain: What value do they add over and above other measures, and, importantly, the measure should not be interpreted in isolation (Gabbett, 2018), with context the key. So, is the acute:chronic workload ratio worth it? In isolation the tool provides little but a number to show isolated training status; however, when used alongside other measures of load, other injury risk factors and contextual factors affecting day-to-day injury risk status, the tool adds value when assessing whether the balance between fitness and fatigue states in that athlete are appropriate. In the context of this thesis, the importance of understanding context in the decision-making process can be seen when comparing the results of Chapter Four and Chapter Six. In isolation, using the acute:chronic workload ratio (albeit at a team level), would indicate the importance of avoiding spikes in the acute:chronic value (Chapter Four), and, therefore, coaches may be more wary of high rather than low values. However, as soon as this data is contextualised by adjusting for other risk factors such as previous injury, previous concussion and cumulative match minutes (Chapter Six), those players who were being "protected" in Chapter Four may now be at a greater risk of injury through exposure to low acute:chronic load values. This is just one example of how providing context (in this case through adjusting for other risk factors) is essential when using training load data in decision making process. The key for any coach will be to filter the signal from the noise and make informed contextualised choices using the data to guide decisions, not make them.

This thesis clearly demonstrates the complexity involved in the use of the acute:chronic workload ratio. This complexity not only stems from the potential number of the methods used to calculate the value (Chapter 5) but also in the changing meaning of the data when accounting for other potentially important risk factors (Chapter 6 and 8). Recent debate surrounding the validity of the method has questioned not only the methods by which the measure is calculated (Wang et al., 2019) but also whether the evidence surrounding the proposed 'sweet spot' is in fact reliable (Impellizzeri et al., 2019b). While this thesis provides the largest studies to investigate the training load and injury relationship, given the variation seen between clubs (Chapter 5) as well as the contrasting results found between team level (Chapter 4) and individual data (Chapter 6), it is with caution that the results be implemented in a club setting. Aside from the variation between clubs and individual/team data, other methodological challenges remain. For example, within Chapter 5, the coupled method of calculation was deemed to be the most appropriate method for data aggregation, however, recent critiques appear to demonstrate that coupled loads are an unsupported method given the spurious correlations associated with them (Lolli et al., 2017; Wang et al., 2019). While addressing as many of the potential challenges raised concerning the acute:chronic method within this thesis, limitations in the data are presented and discussed in each chapter. The acute:chronic workload ratio remains a widely used tool in elite sport to manage athletes but given the mounting evidence to question its validity as well as the club–by-club and potentially player-by-player individuality, the use of other methods such as week–to-week changes may offer more reproducible methods for future monitoring strategies (Lazarus et al., 2017).

9.4.2.2 A 3:14 day exponentially weighted acute:chronic workload ratio

In Chapters Six and Eight of this thesis, the acute:chronic workload ratio was calculated by 3 to 14 day exponentially weighted and coupled load value. The selection of these were driven by the results from Chapters Five and Eight, respectively. While these values represented the best fit models, using area under the curve (AUC) as the criterion measure, it is important to consider the implications and practicality of these calculation methods. The value of around 1.25 (the 75th percentile of acute:chronic values) represented a lower risk than that at the lower (0-25th percentiles) and upper ends (nearing the 100th percentile) of the acute:chronic scale. This indicates that athletes need to ensure that they do not do too much, or too little. In the context of this thesis, this concept of “too little, too much” was confirmed, but over a shorter time frame (3 to 14 days), with athletes doing “too little” being at a greater risk than those doing “too much”. While not undertaken for each load variable, to assess if this low acute:chronic value finding was an artefact of the calculation method alone, a 7:28 day time frame using sRPE data was also assessed, in which a similar relationship remained (Chapter Eight).

While the 3:14 day metric showed the greatest association with injury risk, is it practical to apply this ratio? In the case of match-related injury for instance, where a player is likely to take part in a heavy session two to three days prior to a game and a light “captain’s run” the day before, that heavy session is the primary stimulus during that crucial three-day window. As highlighted in Chapter Six, low acute:chronic values may represent a player who is unable to take part fully in training in the build-up to a game, yet is still fit to play in the game itself. Should this 3-day period be so vital, as suggested in this thesis, unavailability for a training stimulus in the 72 hours before a game presents a difficult situation for coaching staff, recognising that the athlete is at significantly higher injury risk come match day. These kinds of decisions, to play or not play athletes are common scenarios in professional sport and their outcome relies on the philosophy of the sports medicine team regarding the use of workload metrics to guide decision making, as well as contextual factors such as the importance of the player and the match. Alternatively, this questions the applicability of a 3 day acute and 14 day chronic period, with a load on the fourth day prior to an injury leaving an athlete with a very different risk to that of the same load experienced a day later. While the evidence was clear in Chapter Five that this 3 to 14 period was appropriate, physiologically and practically, coaching staff must consider the impact of specific time periods on acute:chronic calculation. They are likely to be sport specific and potentially even training or tissue specific, so the inclusion of all training types in Chapter Five may be an oversimplification of complex human physiology. For example, in the context of other sports such as endurance running, a 14 day chronic load is likely to tell a coach very little about the physical fitness of the athlete and it may be appropriate to consider load not in days, but weeks, months or years. What is clear is that there is a link between training load and injury risk using a 3:14 day acute:chronic workload ratio in professional rugby; however, what is not clear is whether these time periods provide staff with enough time to execute positive changes on an athlete's risk profile, and, therefore, either more practical time periods or potentially different measures of load may offer more utility.

Aside from the use of 3 and 14 day time periods in the calculation of acute:chronic workload ratios, the same acute and chronic time periods were examined in isolation as risk factors. Previously, when examined as isolated risk factors, the acute and chronic time periods used are often longer in duration (typically 7 to 28 days). It is possible, however, that these arbitrary values used in previous research are not sports specific. It may, therefore, be desirable to set these values over longer periods to coincide with the micro or macro cycles of the club; however, this is likely to be specific to the periodisation programmes for each individual club. In this study the cut-points associated with each acute or chronic threshold were set based on equal observations in each category. However, in future work it may provide more valuable data if arbitrary cut points were selected based on the values of interest to a team or coach. The use of these acute and chronic load values may offer utility when combined with other variables of interest, to establish changing risk profiles dependant on either high or low levels of chronic load for example, and should be explored in this setting in future research.

9.4.2.3 Load management: Is it worth the effort?

Irrespective of the measurement a club collects, or the way in which they analyse the data, in a world where resources are finite, is the expense, time and effort worth the value provided by load monitoring? Current monitoring protocols in rugby union are a burden to staff, athletes and those financing the clubs. Financially, the cost of managing athletes' loads can range from nothing, in the case of just sRPE and Microsoft Excel, to hundreds of thousands of pounds annually with athlete management systems, GPS units, heart rate monitors and multiple other tools possible for data collection. Additionally, the time investment from practitioners to capture, aggregate, analyse, interpret, summarise and often visualise the data takes away from the job they are there to do. Therefore, when comparing load management to other important components in a high performing sports organisation, such as medical staff, conditioning staff, coaches and managers, load monitoring falls into the category of "nice to have" and not "need to have". While this view may seem contrary to the essence of this thesis, it must be recognised that not only in the context of sport, but particularly in rugby union, injury is likely to be inevitable over a career, irrespective of a players' load values. This was exemplified in a recent study, whereby although training loads were built chronically over time to remain within the reported acute:chronic workload ratio sweet spot, a running related injury was the eventual outcome (Hulme et al., 2018). While this was conducted in a synthetic sample, it is only representative of what is likely to be seen every day whereby coaches see athletes sitting in training zones deemed to be safe and yet they get injured. So, should it be the case that a club must choose between medical cover during training compared to load management, it is difficult to argue in favour of load management; however, if all other necessary pieces of the puzzle are in place, then athlete monitoring provides a valuable addition for a sports medicine team to make more informed decisions about player injury risk. It is also important to remember that in the world of professional sport, a monitoring tool that can prevent one injury per season in a player being paid £100,000 per week pays for itself in lost wages if that injury was to occur.

9.4.2.4 Load management: Who's asking?

When interpreting the results of this thesis, it is important to understand the context by which you are interpreting them and your role in sport, with coaches driven by performance, yet governing bodies striving for improved player welfare. As outlined in Chapter Four, performance in team sport is challenging to account for when building these model types, as good team performances can lead to poor team outcomes, and vice versa. It is for this reason that when findings in training load and injury risk studies indicate a reduced load may decrease injury risk, it must also be considered that dramatically reducing a player's load is also likely to reduce their overall performance levels. While this may be more pronounced in some contexts, such as endurance sport, the same case may be made for rugby union. For instance, reducing training exposure may limit injury risk but also may leave athletes physically unprepared for the demands of the sport and lacking the technical quality to compete.

Although player availability was measured and accounted for in Chapter Four of this study, with unclear findings, the perspective from which you view these findings is important. As a governing body or employer, with responsibility to maintain player welfare (Webborn, 2012), player availability is an important metric to gauge the burden of injury and inform policy makers on the necessary squad sizes required to compete at the top level of club rugby. If, however, you view player availability from a club coaching perspective, the relative importance of that player to the squad in value, personality or position, makes athlete availability more context specific. In this sense, having player availability of 95% (considered very good) may not be useful if the 5% you are missing are your key players; however, if you have 60% availability (considered very poor) with that missing 40% being fringe or developmental players, then this may not be an immediate concern. A similar concept of player importance and value is demonstrated through examining the contributing factors to injury burden. Injury burden measures both injury severity and injury incidence and, therefore, the same injury burden value can be made of a large number of injuries with low severity or a small number of injuries with high severity. Given this, in a situation where two teams demonstrate equal injury burden, one driven by high incidence, and one driven by high severity, depending on the relative importance of the players that are injured, one scenario may be more desirable than the other for a coach (Fuller, 2018). While a high burden is not desirable in either case, should the burden be made up of key players, a more short-term loss of those players might be desirable over that of losing a key player for an extended period. However, should the burden be made up by players of less relative importance to team performance, whether the incidence or severity is driving the increased burden may be less important. This difference in individual player value to either a coach for their weekly performance or a governing body for general athlete welfare adds further complexity and challenges to implementing findings such as those seen within this thesis.

9.5 Future Directions

The field of training load and injury risk is rapidly evolving and is likely to continue on that trajectory, with practitioners and researchers alike looking for the next "big step". Although athlete monitoring is becoming increasingly common in an effort to improve player welfare, certainly with respect to rugby, the injury rates are not changing to reflect this (Kemp et al., 2019). It is, therefore, likely that the next step in this area of research will need to drastically move towards more complex and rigorous analytical methods or greater capability of load capture tools to more accurately detect changing risk. To illustrate some potential avenues of exploration, the following recommendations have been divided into those for research and practice.

9.5.1 For Research

One simple and small step to move this field forward would be to add to the types of loads being captured. This thesis focused specifically on the physical loads encountered by players, which was necessary and novel. However, the addition of not only other physical load measures (e.g., accurate contact based measures accounting for the high contact nature of the sport) but also changing the focus from physical measures to those which may identify unique responses to physical load, including psychological and social loads (Quarrie et al., 2016), may add substantial value. With ever growing demands on players for social engagement with fans, media and other groups, and the increased pressure to succeed in a result driven business, the physical demands of the game may be amplified by other pressures, which places a greater strain on the modern athlete. Although desirable to capture the impact of these other types of non-physical load, within the current large-scale multi-team study design, the feasibility of extending the requirements for data capture is unlikely. This is largely due to the widespread differences in current data monitoring tools and methods used by clubs, so should common methods be achieved throughout the clubs, the burden of data capture by clubs and synthesis by researchers can be minimised to make such a large-scale load piece more feasible. This type of a study, where multiple elements of player load including internal and external physical loads, psychological loads, player wellness and travel load to name a few, are currently best suited to a smaller population within single teams or organisation; however; collaboration between teams using similar methodologies is widely accepted as an avenue for exploration.

From a research design perspective, to truly understand the effect of a risk factor such as the acute:chronic workload ratio, the most rigorous experimental design would be a randomised control trial, placing different groups into banded thresholds to measure their effect on subsequent injury risk. While the feasibility of such a study is low, other natural experiments can be used to identify the benefits of certain load management techniques. For example, comparing clusters of teams that do or do not use specific monitoring measures would move towards answering the question of whether the time and effort involved in monitoring is worth it.

Aside from research design, the methods by which we currently analyse data of this type has progressed but is likely to evolve over the coming years. A recent review of analytical approaches to longitudinal load data has shown the wide variety of methods used, with each demonstrating strengths and weaknesses (Windt et al., 2018). While complex and potentially less accessible to those working within sports, machine learning techniques may offer more powerful and robust analysis methods, with their utility recently demonstrated in the context of soccer (Rossi et al., 2018). Despite this, as with any type of a modelling technique in which injury prediction is the outcome, we are limited by the need to place a cost on making errors in our modelling. For example, in the context of withholding a player from a game due to a modelled high-risk injury threshold, the cost of a type I error means a key player could be left out of a team, resulting in performance and financial consequences to the individual and the team. Conversely, the cost of a type II error could leave a key player injured for an extended period. While putting a cost on making these errors is impossible, the consideration for that player are also likely to be influenced by a myriad of other factors including, time in season, importance of fixture, stage of players career and many others. Further to this, the use of a more complex systems approach is likely to offer further insight into changes in injury risk; however, the complexities around this analytical approach are yet to be fully understood. While complex and again potentially less accessible, this approach allows for non-linearity between variables and outcomes, recursive loops and uncertainty to identify regular patterns leading to outcomes of interest (Bittencourt et al., 2016).

A number of recent articles have investigated a host of load variables, capture methods and different sporting populations, but given the drive for new technologies and advanced analytics in a field that is ever evolving, very little time is actually devoted to what optimal load monitoring might look like. Often, people are moving on to the latest trend before evaluating whether the simple things, applied in the correct manner with the right people in place, are best. For example, given the current data dense environment in sport, sports teams are looking to invest in people to analyse the data, who may or may not have the skillset to interpret the findings. It is for these reasons that, rather than moving on to more complex technologies or analytical methods, we should look to see how the tools we already use could make a greater impact. This may be exemplified by the work undertaken in Chapter Eight of this thesis, whereby the addition of more complex, time inefficient and expensive GPS metrics offered no more information than that of a simple sRPE measure for injury risk detection. It may transpire that current monitoring practices are optimal, and we do in fact collect the right measurements and analyse them in the best way, but coming to a greater understanding of how far from optimal we currently are may offer greater insight into what we are missing.

In light of the methodological difficulties currently in place surrounding assessing injury risk in rugby union, and although there is still a great deal to be done in advancing the research in this area, a logical next step in this field would be to incorporate a measure of performance into studies looking at training and injury. Although addressed at a team level in Chapter Four, increasing the sensitivity of the performance measures used to provide more insight into the effect of training on individual performance would be widely welcomed by coaching staff. Although it is difficult to measure performance, consultation with coaches and stakeholders may offer insight into avenues for exploration, to ensure both elements of team success and individual performance are captured. While player welfare and injury risk management remains the number one priority for governing bodies of the sport, shifting the focus of research to incorporate an element of performance is likely to elicit greater engagement from clubs, where the primary focus is performance.

9.5.2 For Practice

Monitoring practices currently used in club settings capture data across a period of time to establish baseline values and a current status for each player. Each day or week, this data will be reviewed by medical, conditioning and coaching staff to manage injury risk, plan training and assess performance. The current processes are, therefore, reactive in nature and respond to changes that training may have on any player. While this is a valuable use of monitoring data on a daily basis, it is likely that this information could be used more proactively to optimise and plan training loads according to a player's historical data. Optimisation is defined as "the task of finding a set of values that maximise an objective function and satisfy a set of constraints" (Carey et al., 2017b). Effective use of optimisation techniques within a training environment can enable conditioning staff to generate preseason training programmes that adhere to a set of evidence-based constraints as defined by the staff, such as the maximum recommended limits on acute or chronic training load (Carey et al., 2017b). The goal of such a procedure could be manipulated to meet the aims of the coaching staff, for example in the case of Carey et al. (2017b), to either maximise total distance achieved prior to a set date or to maximise modelled performance based on the fitness-fatigue relationship outlined by Banister et al. (1975). Prior to such an optimisation technique being undertaken, conditioning staff should establish the desired end-goal of the process and the constraints being used in the optimisation process, while also considering the potential for achieving the same target value using different methods (Carey et al., 2017b). However, this process does provide more proactive methods for using data to help drive adaptation in athletes based on predetermined constraints driven by historical previous data.

Professional sport is driven by performance and results and, therefore, coaches are always looking to stay ahead of the game. In an environment where marginal gains and technology are paramount, the fear of being left behind is pushing monitoring methods and data capture to a tipping point where clubs find themselves in a perpetual state of data cleaning and scrambling for data driven answers to questions that are likely best answered through intuition and coaching experience. It is for this reason that, while we continue to innovate, perhaps a shift in focus may be required to capture less, value what we do collect more and to do the simple things really well. As mentioned previously, within the sports industry it is evident that the role of sports scientists in elite sport is being reduced to data analytics, with a focus on dealing with big data, machine learning and automation. It is clear that skillsets such as these are increasingly more sought after, with little mentioned about context, sporting background or interpretation of results present. Given the lack of substantial evidence for the ability to predict injury in sport, this again raises the question whether investment in people who can interpret and use the data to positively impact upon injury risk over those who seek to build complex models to predict is desirable. Further to this, looking again at simplicity over complexity, in the case of rugby union, whereby contact is a greater determinant of injury risk than running based metrics, the money spent on GPS systems may be better spent on people to code for contact exposure. Given the findings of Chapter Eight, this may be the case.

While some of these future directions may currently be outside of our reach, this field will continue to adapt and, as with all techniques, what is now complex will eventually seem routine. The era of data driven athlete monitoring is here and will continue to pose questions for both research and practice alike. Therefore, as scientists, we should not only continue to provide empirical evidence for what is used in common practice and optimise the utility of this data, but also continue innovating and exploring new avenues.

9.6 Conclusion

This thesis aimed to quantify the influence of training load upon injury risk in professional rugby union. To do this, six novel research questions were posed and investigated within the programme of work.

This thesis represents the largest study of training load and injury risk of its type across all sport, capturing data from 823 unique players (~1400 player seasons) across 13 different clubs over the course of three seasons. It is clear from the findings that the training that an athlete completes does have an influence upon injury risk. While the volume of training per player has not changed over time in professional rugby union, it is likely that the intensity at which it is completed has changed. Despite improvements in knowledge around injury risk management, it would appear that injury risk has not changed substantially over time. Multiple aspects of the athlete monitoring experience in rugby union have been addressed within this thesis including which variables to capture, how to aggregate that data, how to calculate the derived training load metrics and what it means for the modern athlete. What is demonstrated within this thesis is that the aggregation of training data on an individual basis (compared with team averages) provides more practical information to coaches in managing injury risk. Further to this, the methods by which current training load variables (namely the acute:chronic workload ratio) are constructed are not optimal in all cases and, therefore, clubs should consider investigating different methodologies to improve data insights. Furthermore, this thesis has reinforced the importance of other previously documented risk factors, such as previous injury and cumulative match minutes. Finally, this thesis has outlined the relationship between training load and injury risk in rugby union and demonstrated the potential importance of the acute:chronic workload ratio metric in managing injury risk in athletes.

The findings of this study demonstrate the potential for using training load measures to capture and manage injury risk in a professional rugby union population. In doing so, they provide justification for the use of load monitoring tools in rugby union when considered in conjunction with other previously documented risk factors. The impact of this thesis provides objective evidence across multiple clubs for the use of monitoring strategies and provides a pathway by which clubs might look to implement change within their own club settings.

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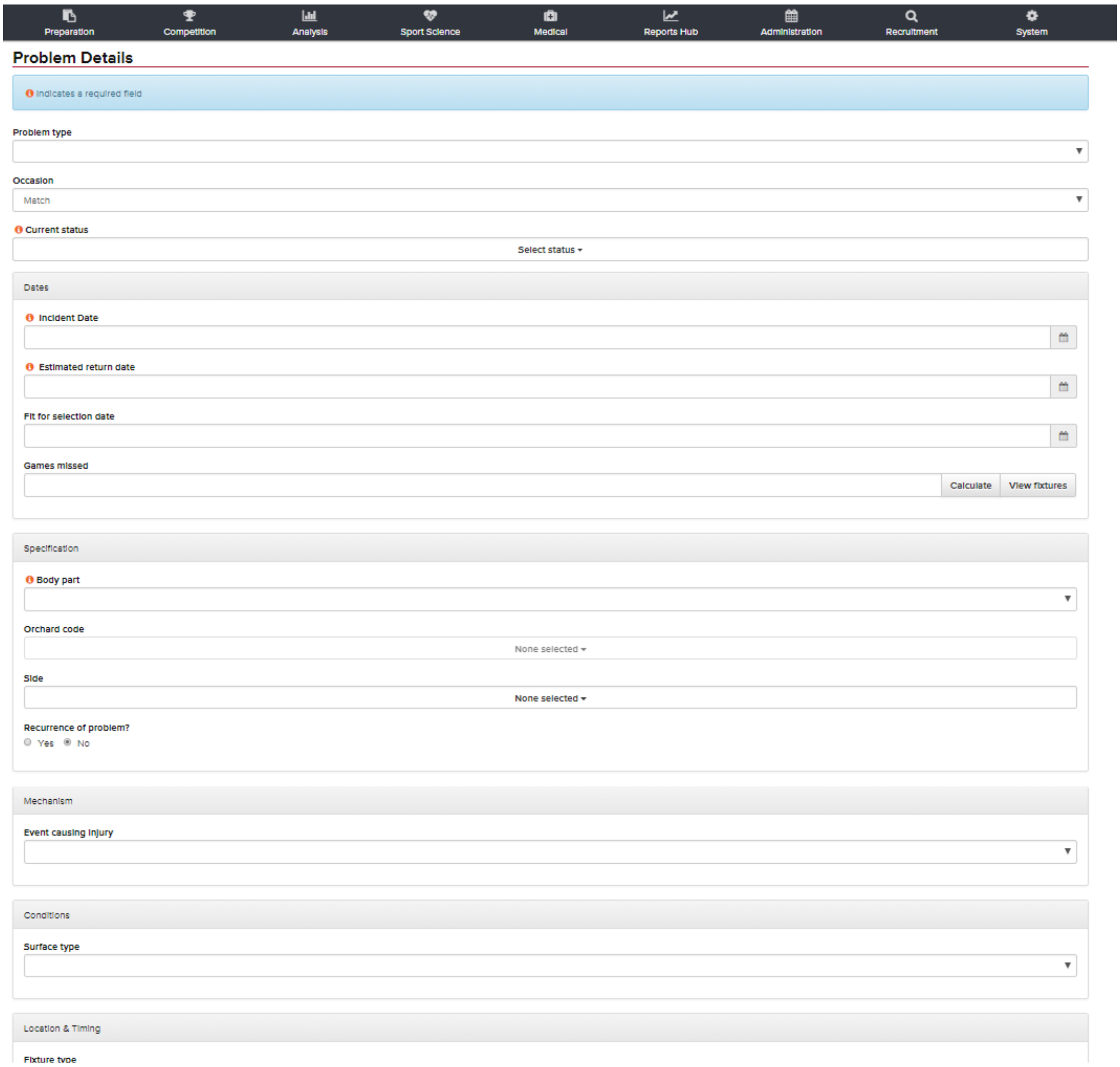
APPENDICES

APPENDIX A:

Match Injury Reporting Form- Rugby Squad Online Platform



Preparation | Competition | Analysis | Sport Science | Medical | Reports Hub | Administration | Recruitment | System

Problem Details

indicates a required field

Problem type

Occasion

Match

Current status

Select status

Dates

Incident Date

Estimated return date

Fit for selection date

Games missed

Calculate | View fixtures

Specification

Body part

Orchard code

None selected

Side

None selected

Recurrence of problem?

Yes No

Mechanism

Event causing injury

Conditions

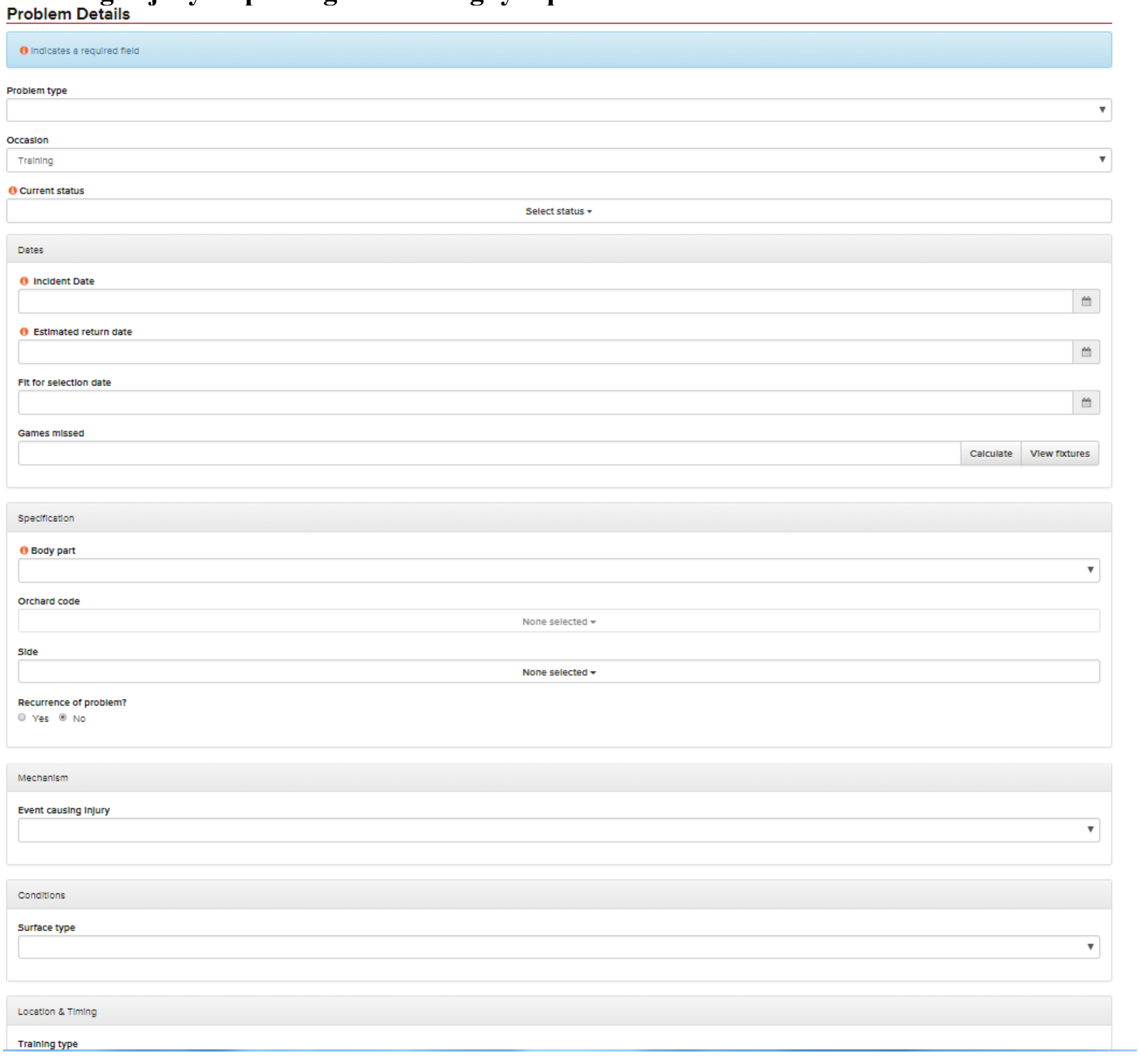
Surface type

Location & Timing

Fixture type

APPENDIX B:

Training Injury Reporting Form- Rugby Squad Online Platform



Problem Details

Indicates a required field

Problem type

Occasion

Training

Current status

Select status

Dates

Incident Date

Estimated return date

Fit for selection date

Games missed

Calculate | View fixtures

Specification

Body part

Orchard code

None selected

Side

None selected

Recurrence of problem?

Yes No

Mechanism

Event causing injury

Conditions

Surface type

Location & Timing

Training type

APPENDIX C:
Injury Surveillance and Training Load Consent and Information Sheet

The English Professional Rugby Injury Surveillance Project

Player Information Sheet

The influence of training and match load on injury and illness in elite rugby union

Principal Investigator: Keith Stokes
Other Investigators: Stephen West, Sean Williams, Simon Kemp

You are invited to take part in a research study that will investigate training and match loads as a risk factor for time-loss and non time-loss injury and illness in elite rugby union. The study is fully supported by the Rugby Football Union, Premiership Rugby and the Rugby Players' Association. This study will be fully aligned with the RFU professional rugby injury surveillance project, this will allow for the collection of time-loss and non time-loss match and training injuries during the competitive season for use in this study. Before deciding whether to take part, it is important that you understand why the study is being undertaken and how it might involve you. Take time to the read the following information carefully; if there are any aspects of the study that you do not understand, please discuss them with a member of your medical team or contact us for further information. When you have read and fully understood the information and you wish to be included in the study, you will be asked to sign a consent form.

Background to the study

A player or team's training load might influence injury risk in rugby union and other collision sport. However, further research with greater numbers of participants is required to fully understand this complex relationship in professional Rugby Union. It is thought that, in the long term, training load and the accumulation of training load over time may also play an important role in the management of overtraining and subsequently career longevity. This study will allow for a better understanding of the management of training load throughout a competitive season and will also contribute to improving player welfare.

The aim of this study is to determine the relationship between training load and the incidence/severity of injury. The information that this study provides will be an important and valued component in the continued development of training programmes for coaches. Data will be collected for this study during the 2018/19 season.

What does the study involve?

Daily training load, match load, time loss and non-time loss injury data as well as illness data will be collected for all full-time contracted players that participate in the study. During the pre-season period, medical personnel at your club will collect the following information from you: date of birth, most common playing position, height, weight, dominant arm, dominant leg and ethnicity. This information will be entered into the online database and will be linked with your injury data.

For further information, or if you have any questions, contact Stephen West, University of Bath. Tel: 01225 385469
or E-Mail: s.west@bath.ac.uk

The English Professional Rugby Injury Surveillance Project

Player Information Sheet

To be able to calculate training load, you will be asked to submit an RPE (Rating of Perceived Exertion) score (on a scale of 1 to 10) within 30 minutes after the end of each training session. The strength and conditioning coach at the club will then submit the duration of each session so that this can be matched to each RPE score to allow a value for training/match load to be calculated. Further to this, global positioning system (GPS) data may be collected from some teams and will also be collated at the University of Bath, after collection by the staff of your club. This will include variables such as high speed running and total distance covered during training and matches. Your time-loss injury and illness data such as incidence, type, severity and causation will be reported by your medical staff using a secure online only medical system. In addition to the collection of these data, the RFU English Professional Rugby Union Injury Surveillance Project will also allow for the collection of non time-loss injury data. These are injuries that require medical attention for but do not cause you to have any absence from match play or training.

This data will be analysed by researchers in the Department for Health at the University of Bath.

Who is being asked to participate in the study?

All first-team-eligible players at English Premiership rugby clubs and England representative teams are being asked to take part in the study.

Do I have to take part?

Participation in the study is voluntary. You do not have to take part in the study but the more players who take part, the more comprehensive the data will be. If you decide to take part, you must sign a consent form that confirms you have been provided with this information and you agree to be included in the study. You are free to withdraw from the study by contacting us at any time without giving a reason. Should you wish to withdraw from the study, your data can be removed from the dataset up to 2 weeks after the completion of each seasons data collection.

Are there any risks from taking part?

There is no increased risk associated with this project over and above your normal rugby activities with the club/ representative team.

Will information about my injuries be kept confidential?

In accordance with the new General Data Protection Regulations (GDPR), we must obtain your permission to collect information about your injuries during the course of this study. All information collected in the study is recorded and stored anonymously using a player identification code on a database at the University of Bath.

What will happen to the data obtained from the research study?

The data collected will be analysed by researchers at the University of Bath to produce summary information about the relationship between training load and the incidence and severity of injury and/or illness. This information may be used by the RFU/Premiership Rugby/RPA for the formation of guidelines for the management of training load in the future.

For further information, or if you have any questions, contact Stephen West, University of Bath. Tel: 01225 385469
or E-Mail: s.west@bath.ac.uk

Player consent form

I confirm that I have read and understood the player information sheet for the above study and that I have had an opportunity to ask questions.

I agree to take part in the above study and give my consent for doctors, physiotherapists and fitness/ conditioning staff to supply medical and training information to the University of Bath. I acknowledge that such information will only be used for research, statistical and other analysis purposes, and that reference to individuals shall not be made in any report or other published material.

I understand that all the information provided on my injuries and training will be treated in strict confidence and will remain anonymous.

I understand that I have the right to withdraw from this study at any stage and that I will not be required to explain my reasons for withdrawing.

I understand that I can ask the researcher to stop using my information up to two weeks after the completion of each season's data collection.

_______________________ __________ _________________

Name Date Signature

For further information, or if you have any questions, contact Stephen West, University of Bath. Tel: 01225 385469 or E-Mail: s.west@bath.ac.uk

APPENDIX D:
Monitoring Questionnaire: Chapter Seven

Premiership GPS Survey

Page 1: Introduction

To whom it concerns,

Many thanks for your continued support with training load (sRPE) and injury risk study, which is coming to the conclusion of the second season of data collection. To further understand the relationship between training load and injury risk, we have been advised by the Sports Science Advisory Group to try and collect some measure of external load to pair with the internal load already collected through sRPE. With this in mind, we are conducting this survey to establish the systems, versions, variables and definitions used across Premiership clubs when collecting and analysing GPS data for both performance measurement and injury management.

We would kindly ask that you complete the survey on the next page to help us understand the landscape of data capture across the Premiership. The results of this survey will be used by the research team for the purposes of establishing what common data elements are present across clubs. All survey responses will be kept confidential with only the research team having access to the results.

Should you have any quesions or concerns about the questionnaire, please get in touch with me at s.west@bath.ac.uk and I will do my best to answer your questions.

Many thanks as always,

Stephen West

PhD Student, University of Bath

1. What is your name? ✱ *Required*

2. What club do you work for? ✱ *Required*

3. I hereby consent to participate in the following survey, with the results being used for research purposes associated with the Professional Rugby Injury Surveillance Project. ✱ *Required*

- [ ] Please tick

Page 2: Questionnaire

4. Please rate how highly you value the following measures for the the management of individual injury risk (1 being highly valued). ✱ *Required*

Please don't select more than 1 answer(s) per row.

Please select at least 11 answer(s).

	1	2	3	4	5	We dont measure this variable.
sRPE	☐	☐	☐	☐	☐	☐
GPS	☐	☐	☐	☐	☐	☐
Heart rate	☐	☐	☐	☐	☐	☐
Collision counts (Tackles, Scrums, Rucks etc)	☐	☐	☐	☐	☐	☐
Neuromuscular function (CMJ, squat jumps etc)	☐	☐	☐	☐	☐	☐
Wellbeing questionnaires	☐	☐	☐	☐	☐	☐
Other subjective ratings	☐	☐	☐	☐	☐	☐
Movement screening	☐	☐	☐	☐	☐	☐
Player age	☐	☐	☐	☐	☐	☐
Player experience	☐	☐	☐	☐	☐	☐
Previous injury history	☐	☐	☐	☐	☐	☐

5. What GPS system provider do you use? ✱ *Required*

- STATSports
- Catapult
- Other

5.a. If you selected Other, please specify:

6. What version of the GPS system do you use? ✱ *Required*

7. Have you recently (within the 16/17 season) changed provider of your GPS units? ✱ *Required*

- Yes
- No

7.a. What previous provider were you with?

8. Have you recently (within the 16/17 season) changed version of your GPS units? ✱ *Required*

- Yes
- No

8.a. What previous version were you using?

9. What model of GPS unit do you use to collect your data? ✱ Required

10. What software do you use to analyse your GPS data? ✱ Required

11. What is the measurement speed of your GPS units? (In Hz) ✱ Required

12. Which variables do you export and use from your GPS system? ✱ Required

- Total distance
- Accelerations
- Decelerations
- Distance in speed zones
- High Speed Running (distance)
- Count of Sprints

- Sprint distance
- Total Loading
- Average velocity
- Player Load
- Dynamic Stress Score
- High Metabolic Power
- Repeated High Intensity Bouts (Count)
- Repeated High Intensity Bouts (Duration)
- Peak velocity
- Meters per minute
- Tackle count
- Other

12.a. If you selected Other, please specify:

13. For training sessions, are the measurements you collect absolute (total session time) or relative (to time in play)? ✱ *Required*

- Absolute
- Relative
- Both
- Other

13.a. If you selected Other, please specify:

14. For matches, are the measurements you collect absolute (total game time) or relative (to time in play)? ✱ *Required*

- [ ] Absolute
- [ ] Relative
- [ ] Both
- [ ] Other

14.a. If you selected Other, please specify:

15. Do the variables recorded for match and training differ? ✱ *Required*

- ○ Yes
- ○ No

15.a. Which variables differ for match and training?

16. On a scale of 1-10 with 1 being the most important, how much do you value GPS data as a measure of player performance? ✱ *Required*

- ○ 1
- ○ 2
- ○ 3

- 4
- 5
- 6
- 7
- 8
- 9
- 10

16.a. Which variable do you place the greatest value on, when assessing performance? ✱ *Required*

17. On a scale of 1-10 with 1 being the most important, how much do you value GPS data to inform the management of injury risk? ✱ *Required*

- 1
- 2
- 3
- 4
- 5
- 6
- 7
- 8
- 9
- 10

17.a. Which variable do you place the greatest value on, when managing injury risk? ✱ *Required*

18. Do you use absolute (same for the whole team) or relative (individualised to players max velocity) speed bands for GPS speed zone calculations? ✱ *Required*

- Absolute
- Relative
- Both
- Other

18.a. If you selected Other, please specify:

19. What speeds are your speed zones categorised into? e.g. answer. Zone 1: 0.5-1m/s, Zone 2: 1-2m/s, Zone 3: 2-3m/s, Zone 4: 3-4m/s, Zone 5: 4-5m/s, Zone 6: 5-10m/s ✱ *Required*

20. What percentages of max velocity are your relative zones categorised into? e.g. answer. Zone 1: 0-30%, Zone 2: 30-60%, Zone 3: 60-70%, Zone 4: 70-80%, Zone 5: 80-90%, Zone 6: 90-100% ✱ *Required*

21. What speed do you classify as high speed running? ✱ *Required*

22. What speed do you class as sprinting? ✱ *Required*

23. Do you record a measure of contact (e.g. number of tackles) during training for your players? ✱ *Required*

- Yes
- No

23.a. How do you record contact events during training?

- GPS derived metrics
- Video analysis
- Other

23.a.i. If you selected Other, please specify:

24. Do you record a measure of contact (e.g. number of tackles) during matches for your players? ✱ *Required*

- ○ Yes
- ○ No

24.a. How do you record contact events during games?

- ☐ GPS derived metrics
- ☐ Video Analysis
- ☐ Not applicable
- ☐ Other

24.a.i. If you selected Other, please specify:

25. What sessions do you record? ✱ *Required*

- ○ All training sessions (indoor and outdoor)
- ○ All outdoor sessions
- ○ Matches only
- ○ Other

25.a. If you selected Other, please specify:

26. How many GPS units have you got access to? ✱ *Required*

27. What are the barriers to the collection of GPS data within your club? ✱ *Required*

- ☐ Lack of equipment
- ☐ No consensus on best practice for analysis
- ☐ Validity and reliability of measurement tools
- ☐ Coach "buy-in"
- ☐ Manpower required to analyse data
- ☐ Other

27.a. If you selected Other, please specify:

27.b. On a scale of 1-10 (1 being no limitation at all, 10 being highly limiting), how much do these factors limit your ability to collect and use GPS data on a day to day basis? ✱ *Required*

- 1
- 2
- 3
- 4
- 5
- 6
- 7
- 8
- 9
- 10

28. Which players do you capture GPS for? ✱ *Required*

- All players
- All senior squad players
- Key players only
- Other

28.a. If you selected Other, please specify:

Page 3: Thank you

Many thanks for completing the survey for us. If you have any questions or would like to know more about the study, please get in touch with me at s.west@bath.ac.uk

APPENDIX E:

Supplementary Data: Chapter Five

Supplementary table 1: AUC values by season

			Coupled				Uncoupled			
2015-16			14	21	28	35	14	21	28	35
	RA_INJ	3	0.55	0.54	0.53	0.53	0.54	0.54	0.54	0.54
		5	0.55	0.55	0.55	0.55	0.52	0.52	0.52	0.52
		7	0.53	0.51	0.51	0.52	0.50	0.51	0.51	0.50
		9	0.55	0.54	0.52	0.53	0.52	0.52	0.52	0.52
	EWMA_INJ	3	0.68	0.68	0.67	0.66	0.56	0.54	0.53	0.53
		5	0.64	0.65	0.65	0.65	0.56	0.54	0.53	0.52
		7	0.61	0.62	0.62	0.62	0.55	0.53	0.52	0.51
		9	0.59	0.60	0.60	0.61	0.55	0.53	0.52	0.51
2016-17			14	21	28	35	14	21	28	35
	RA_INJ	3	0.61	0.60	0.60	0.60	0.54	0.54	0.54	0.54
		5	0.55	0.56	0.55	0.55	0.52	0.52	0.52	0.52
		7	0.54	0.52	0.52	0.52	0.51	0.51	0.51	0.50
		9	0.55	0.52	0.51	0.52	0.52	0.52	0.52	0.52
	EWMA_INJ	3	0.68	0.68	0.67	0.67	0.56	0.54	0.53	0.52
		5	0.66	0.66	0.66	0.65	0.56	0.54	0.53	0.52
		7	0.63	0.63	0.63	0.63	0.55	0.53	0.52	0.51
		9	0.60	0.62	0.62	0.62	0.55	0.53	0.52	0.51

Supplementary Figure 2: AUC by club

			Coupled				Uncoupled			
Club 1			14	21	28	35	14	21	28	35
	RA_INJ	3	0.59	0.60	0.60	0.61	0.59	0.60	0.60	0.60
		5	0.63	0.64	0.64	0.64	0.62	0.63	0.63	0.63
		7	0.59	0.60	0.60	0.60	0.59	0.59	0.59	0.59
		9	0.57	0.58	0.58	0.59	0.58	0.59	0.58	0.58
	EWMA_INJ	3	0.72	0.71	0.71	0.71	0.66	0.67	0.68	0.68
		5	0.69	0.69	0.69	0.69	0.62	0.63	0.64	0.65
		7	0.68	0.68	0.67	0.67	0.60	0.60	0.62	0.62
		9	0.67	0.67	0.66	0.66	0.59	0.58	0.60	0.61
Club 2			14	21	28	35	14	21	28	35
	RA_INJ	3	0.59	0.60	0.60	0.60	0.59	0.60	0.60	0.60
		5	0.63	0.64	0.64	0.64	0.62	0.64	0.63	0.63
		7	0.59	0.60	0.60	0.60	0.59	0.60	0.60	0.59
		9	0.58	0.58	0.58	0.59	0.58	0.59	0.59	0.58
	EWMA_INJ	3	0.72	0.71	0.71	0.71	0.66	0.67	0.68	0.68
		5	0.69	0.69	0.69	0.69	0.63	0.64	0.64	0.65
		7	0.68	0.68	0.67	0.67	0.61	0.62	0.62	0.63
		9	0.67	0.67	0.67	0.66	0.60	0.61	0.61	0.61
Club 3			14	21	28	35	14	21	28	35
	RA_INJ	3	0.60	0.60	0.60	0.61	0.59	0.60	0.60	0.60
		5	0.63	0.64	0.64	0.64	0.62	0.63	0.63	0.63
		7	0.58	0.59	0.60	0.60	0.59	0.59	0.59	0.59
		9	0.57	0.58	0.58	0.59	0.58	0.59	0.58	0.58
	EWMA_INJ	3	0.72	0.71	0.71	0.71	0.65	0.67	0.68	0.68
		5	0.69	0.69	0.69	0.69	0.61	0.62	0.64	0.65
		7	0.68	0.68	0.67	0.67	0.58	0.60	0.62	0.62
		9	0.67	0.67	0.67	0.66	0.57	0.58	0.60	0.61
Club 4			14	21	28	35	14	21	28	35
	RA_INJ	3	0.59	0.60	0.61	0.61	0.59	0.60	0.61	0.61
		5	0.63	0.64	0.64	0.64	0.62	0.64	0.63	0.63
		7	0.59	0.60	0.60	0.60	0.59	0.60	0.60	0.60
		9	0.57	0.58	0.58	0.59	0.58	0.59	0.59	0.59
	EWMA_INJ	3	0.71	0.71	0.71	0.71	0.66	0.67	0.68	0.68
		5	0.69	0.69	0.69	0.68	0.63	0.64	0.64	0.65
		7	0.68	0.68	0.67	0.67	0.61	0.62	0.62	0.63
		9	0.67	0.67	0.66	0.66	0.60	0.60	0.61	0.61
Club 5			14	21	28	35	14	21	28	35
	RA_INJ	3	0.59	0.60	0.60	0.61	0.59	0.60	0.60	0.60
		5	0.63	0.64	0.64	0.64	0.62	0.63	0.63	0.63
		7	0.59	0.60	0.60	0.60	0.59	0.59	0.59	0.59
		9	0.57	0.58	0.58	0.59	0.58	0.58	0.58	0.58
	EWMA_INJ	3	0.72	0.71	0.71	0.71	0.66	0.67	0.68	0.68
		5	0.69	0.69	0.69	0.69	0.61	0.63	0.64	0.65
		7	0.68	0.68	0.67	0.67	0.59	0.61	0.62	0.63
		9	0.67	0.68	0.66	0.66	0.57	0.59	0.60	0.61
Club 6			14	21	28	35	14	21	28	35
	RA_INJ	3	0.59	0.60	0.60	0.61	0.59	0.60	0.60	0.60
		5	0.63	0.64	0.64	0.64	0.62	0.63	0.63	0.63
		7	0.59	0.60	0.60	0.60	0.59	0.59	0.59	0.60
		9	0.57	0.58	0.58	0.59	0.58	0.58	0.58	0.59
	EWMA_INJ	3	0.71	0.71	0.71	0.71	0.66	0.67	0.67	0.68
		5	0.69	0.69	0.68	0.68	0.64	0.64	0.64	0.65
		7	0.68	0.67	0.67	0.67	0.60	0.61	0.62	0.63
		9	0.67	0.67	0.66	0.66	0.58	0.59	0.60	0.61
Club 7			14	21	28	35	14	21	28	35
	RA_INJ	3	0.59	0.59	0.58	0.58	0.60	0.60	0.60	0.60
		5	0.62	0.61	0.59	0.58	0.62	0.63	0.63	0.63
		7	0.55	0.51	0.50	0.50	0.59	0.60	0.60	0.59
		9	0.56	0.55	0.52	0.52	0.58	0.59	0.59	0.58
	EWMA_INJ	3	0.66	0.66	0.66	0.66	0.66	0.66	0.67	0.67
		5	0.64	0.63	0.63	0.62	0.59	0.60	0.64	0.64
		7	0.64	0.62	0.61	0.60	0.56	0.59	0.51	0.61
		9	0.67	0.60	0.59	0.58	0.53	0.57	0.59	0.51

			Coupled				Uncoupled			
Club 8			14	21	28	35	14	21	28	35
	RA_INJ	3	0.60	0.60	0.61	0.61	0.59	0.60	0.61	0.60
		5	0.63	0.64	0.64	0.64	0.62	0.63	0.63	0.63
		7	0.58	0.59	0.60	0.60	0.59	0.60	0.60	0.60
		9	0.58	0.58	0.58	0.59	0.58	0.59	0.59	0.59
	EWMA_INJ	3	0.71	0.71	0.71	0.71	0.65	0.67	0.68	0.68
		5	0.69	0.68	0.68	0.68	0.61	0.63	0.64	0.65
		7	0.68	0.67	0.67	0.67	0.58	0.60	0.62	0.62
		9	0.67	0.67	0.66	0.66	0.56	0.58	0.60	0.61
Club 9			14	21	28	35	14	21	28	35
	RA_INJ	3	0.58	0.59	0.58	0.59	0.59	0.58	0.58	0.60
		5	0.63	0.64	0.64	0.64	0.63	0.63	0.63	0.63
		7	0.58	0.60	0.60	0.60	0.59	0.60	0.60	0.60
		9	0.58	0.58	0.58	0.59	0.58	0.59	0.59	0.59
	EWMA_INJ	3	0.69	0.68	0.69	0.69	0.66	0.67	0.68	0.68
		5	0.67	0.67	0.67	0.67	0.63	0.64	0.64	0.65
		7	0.66	0.66	0.66	0.66	0.62	0.62	0.62	0.63
		9	0.66	0.65	0.66	0.66	0.61	0.60	0.60	0.61
Club 10			14	21	28	35	14	21	28	35
	RA_INJ	3	0.52	0.51	0.51	0.52	0.59	0.60	0.60	0.60
		5	0.63	0.64	0.64	0.64	0.62	0.63	0.63	0.63
		7	0.58	0.60	0.60	0.60	0.59	0.59	0.59	0.59
		9	0.53	0.55	0.58	0.58	0.58	0.59	0.58	0.58
	EWMA_INJ	3	0.63	0.62	0.61	0.60	0.64	0.66	0.67	0.68
		5	0.59	0.58	0.57	0.57	0.63	0.64	0.64	0.65
		7	0.57	0.57	0.56	0.56	0.62	0.61	0.62	0.62
		9	0.57	0.56	0.56	0.56	0.59	0.58	0.60	0.61
Club 11			14	21	28	35	14	21	28	35
	RA_INJ	3	0.59	0.60	0.61	0.61	0.60	0.60	0.60	0.60
		5	0.63	0.64	0.64	0.64	0.62	0.63	0.63	0.63
		7	0.58	0.59	0.60	0.60	0.59	0.59	0.59	0.59
		9	0.56	0.58	0.58	0.59	0.58	0.59	0.58	0.58
	EWMA_INJ	3	0.71	0.71	0.71	0.71	0.66	0.67	0.68	0.68
		5	0.69	0.69	0.69	0.69	0.64	0.64	0.64	0.65
		7	0.68	0.68	0.67	0.67	0.62	0.62	0.62	0.63
		9	0.67	0.67	0.67	0.66	0.61	0.61	0.61	0.61
Club 12			14	21	28	35	14	21	28	35
	RA_INJ	3	0.60	0.60	0.60	0.60	0.59	0.60	0.60	0.60
		5	0.62	0.64	0.64	0.64	0.62	0.63	0.63	0.63
		7	0.57	0.60	0.60	0.60	0.59	0.59	0.59	0.59
		9	0.56	0.58	0.58	0.59	0.58	0.58	0.58	0.58
	EWMA_INJ	3	0.70	0.71	0.71	0.71	0.65	0.67	0.68	0.68
		5	0.68	0.69	0.69	0.69	0.59	0.62	0.64	0.64
		7	0.67	0.67	0.67	0.67	0.56	0.59	0.61	0.62
		9	0.67	0.67	0.67	0.66	0.53	0.57	0.59	0.61
Club 13			14	21	28	35	14	21	28	35
	RA_INJ	3	0.59	0.60	0.60	0.60	0.59	0.60	0.60	0.60
		5	0.63	0.64	0.64	0.64	0.62	0.63	0.63	0.63
		7	0.59	0.60	0.60	0.60	0.60	0.59	0.60	0.59
		9	0.57	0.58	0.58	0.59	0.58	0.59	0.58	0.58
	EWMA_INJ	3	0.71	0.71	0.71	0.71	0.65	0.67	0.67	0.68
		5	0.69	0.69	0.69	0.69	0.61	0.62	0.64	0.65
		7	0.68	0.68	0.67	0.67	0.58	0.60	0.61	0.62
		9	0.67	0.67	0.66	0.66	0.56	0.56	0.60	0.61

APPENDIX F:

Supplementary Data: Chapter Six

Week-to-week change and all injury risk

Supplementary Table 2: Effect of training load adjusted for acute load, chronic load, previous injury, previous concussion and 12 month exposure to match play. Injury Hazard: risk per player per exposure day. Likelihood of increased risk of injuries: * possibly, ** likely, ***very likely, ****most likely

Injury Measure	Training Load Variable	Quartile	WTWC Value	Injury Hazard %	Hazard Ratio (90% CIs)
		0	-315	0.4	0.4 (0.1 – 2.0)
		0.25	-20	1.1	1.0 (0.8-1.3)
All Injury	WTWC	Median (Ref)	-1	1.1	1.0
		0.75	14	1.1	1.0 (0.8-1.3)
		1	193	0.6	0.5 (0.2-1.2)

Week-to-week change and non-contact soft tissue injury risk

Supplementary Table 3: Effect of training load adjusted for acute load, chronic load, previous injury, previous concussion and 12 month exposure to match play. Injury Hazard: risk per player per exposure day. Likelihood of increased risk of injuries: * possibly, ** likely, ***very likely, ****most likely

Injury Measure	Training Load Variable	Quartile	WTWC Value	Injury Hazard %	Hazard Ratio (90% CIs)
		0	-315	15.8	52.7 (2.4 – 1162.4) ***
		0.25	-20	0.3	1.0 (0.6-1.6)
All Injury	WTWC	Median (Ref)	-1	0.3	1.0
		0.75	14	0.3	1.0 (0.6-1.6)
		1	193	0.5	1.7 (0.3-8.1)

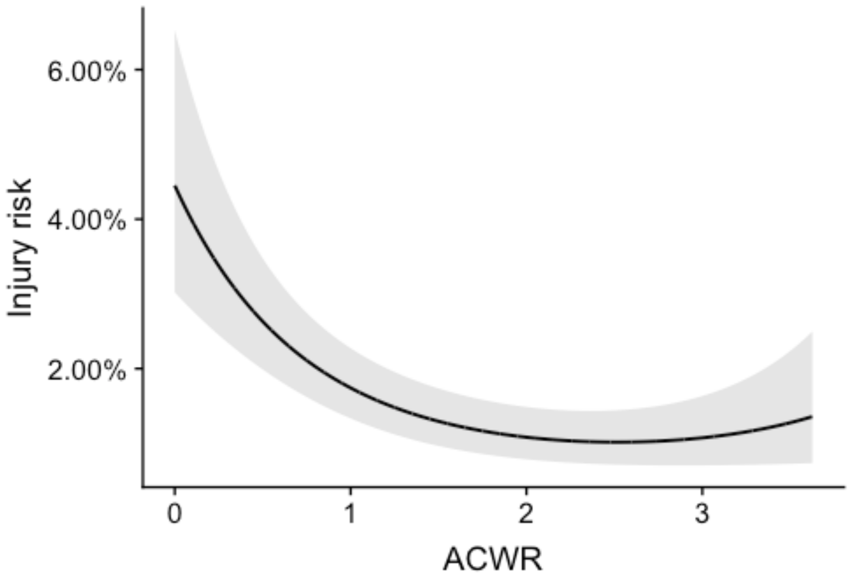
APPENDIX G:
Supplementary Data: Chapter Eight

Supplementary Table 4: Univariate analysis of previous documented injury risk factors

Variable	Category	Unit	Relative Risk (90% CIs)	P-Value	MBI
Position	Back 3 (Ref)	Back 3 (Ref)	1.0		
	Centres	Centres	0.95 (0.70-1.29)	0.78	Unclear
	Half Backs	Half Backs	0.69 (0.51- 0.95)	0.05	Likely Beneficial
	Back Row	Back Row	0.72 (0.54-0.96)	0.07	Likely Beneficial
	Second Row	Second Row	0.91 (0.67-1.23)	0.61	Unclear
	Front Row	Front Row	0.82 (0.62-1.08)	0.23	Possibly Beneficial
Age	Low	18-22 (Ref)	1.0		
	Mod Low	23-25	0.92 (0.73-1.15)	0.52	Unclear
	Mod High	26-29	0.97 (0.79-1.20)	0.83	Unclear
	High	30-36	0.92 (0.72-1.18)	0.58	Unclear
Previous Injury	Low	0	0.01 (0.001- 0.03)	<0.01	Most Likely Beneficial
	Mod Low	1	1.0		
	Mod High	2	1.41 (1.15-1.72)	<0.01	Very Likely Harmful
	High	4-15	3.20 (2.69-3.80)	<0.01	Most Likely Harmful
Previous Concussion	No	No (Ref)	1.0		
	Yes	Yes	1.76 (1.53-2.02)	<0.01	Most Likely Harmful
Match Minutes	Low	0-296	0.74 (0.61-0.89)	<0.01	Very Likely Beneficial
	Mod Low	297-665 (Ref)	1.0		
	Mod High	666-1172	1.10 (0.93-1.31)	0.34	Possibly Trivial
	High	1173-2452	1.18 (0.97-1.42)	0.16	Possibly Harmful

Supplementary Table 5: Acute:chronic workload ratio calculated using 7 to 28 day time periods. Main effect of acute:chronic workload ratio (ACWR) values on injury risk. Injury Hazard represents risk of injury per player per exposure day. Likelihood of change in risk of injuries: * possibly, ** likely, ***very likely, ****most likely. AUC: Area under the curve.

Training Load measure	Training Load Metric	Quartile	ACWR Value	Injury Hazard % (90% CIs)	Hazard Ratio (90% CIs)	Model AUC
sRPE	ACWR (7: 28 day exponentially weighted average)	0	0	4.3 (3.4-5.1)	2.4 (1.9-3.0)****	0.75
		0.25	0.49	2.6 (2.1-2.9)	1.4 (1.1-1.7)***	
		Median (Ref)	0.91	1.9 (1.7-2.1)	1.0	
		0.75	1.19	1.5 (1.3-1.7)	0.8 (0.7-0.9)**	
		1	3.62	1.4 (0.8-1.8)	0.7 (0.5-1.1)	



Supplementary Figure 2: Relationship between Injury risk (Y-axis) and 7: 28 day acute:chronic workload ratio (ACWR) (X-axis). Injury risk represented by injury hazard: risk per player per exposure day.